SAND98-2652C

ADAPTIVE REMOTE-SENSING TECHNIQUES IMPLEMENTING SWARMS OF MOBILE AGENTS

Keith M. Stantz, Robert B. Asher, Stewart M. Cameron, Guillermo M. Loubriel,
Rush D. Robinett, Mike W. Trahan, John S. Wagner

Sandia National Laboratories
P.O. Box 5800, MS-1188
Albuquerque, NM 87185, USA

Abstract

In many situations, stand-off remote-sensing and hazard-interdiction techniques over realistic operational areas are often impractical and difficult to characterize. An alternative approach is to implement an adaptively deployable array of sensitive agent-specific devices. Our group has been studying the collective behavior of an autonomous, multi-agent system applied to chem/bio detection and related emerging threat applications. The current physics-based models we are using coordinate a sensor array for multivariate signal optimization and coverage as realized by a swarm of robots or mobile vehicles. These intelligent control systems integrate globally operating decision-making systems and locally cooperative learning neural networks to enhance real-time operational responses to dynamical environments examples of which include obstacle avoidance, responding to prevailing wind patterns, and overcoming other natural obscurants or interferences. Collectively, sensor neurons with simple properties, interacting according to basic community rules, can accomplish complex interconnecting functions such as generalization, error correction, pattern recognition, sensor fusion, and localization. Neural nets provide a greater degree of robustness and fault tolerance than conventional systems in that minor variations or imperfections do not impair performance. The robotic platforms would be equipped with sensor devices that perform optical detection of biologicals in combination with multivariate chemical analysis tools based on genetic and neural network algorithms, laser-diode LIDAR analysis, ultra-wideband short-pulsed transmitting and receiving antennas, thermal imaging sensors, and optical communication technology providing robust data throughput pathways. Mission scenarios under consideration include ground penetrating radar (GPR) for detection of underground structures, airborne systems, and plume migration and mitigation. We will describe our research in these areas and give a status report on our progress.

1 INTRODUCTION

The ability of the United States to control emerging threats and to verify nonproliferation treaty activities is diminishing. This report addresses aspects of this problem, devises a technical solution, and ultimately implements this solution to counter or thwart these threats and enforce treaty resolutions.

The Problem. United States strategic doctrine is predicated on a technologically superior intelligence apparatus to protect global interests and aggressively preempt emerging challenges to national security. To date, reconnaissance has been dominated by stand-off (long-distance) remote-sensing technologies, satellites and radar systems (e.g., UWAC). Typically, protocol dictates that, first, global activity is assessed, then some level of human intervention is initiated. This methodology is wrought with weaknesses in which leaders of hostile countries and international as well as national terrorists are finding ways to circumvent. As an example, selective concealment of illicit NBC weapons capability is increasingly employed by adversaries in the aftermath of the Gulf War. By constructing underground facilities and detaining weapon inspectors, direct observation by satellite or airborne reconnaissance overflight assets and scientific scrutiny are thwarted. As a result, the above mentioned reconnaissance tools are increasingly less useful because of their limited ability to sense ("smell") chemical and biological agents, to measure ("feel") what sort of activity is occurring, to image ("see") the subtleties of its environment, to assess ("think") the situation, and to adapt ("react") to such an environment. To anticipate and preempt emerging threats and comply with US laws and international treaties necessitates close-up information, collective intelligence, autonomous un-manned covert methodologies, quick response-times, and immunity to countermeasures. Strong motivation exists to deploy semi-autonomous, ground- and air-based, sensing networks in combination with secure theatre communication nodes.

A Solution. A complimentary approach to detection methods can be broken-down into three steps. One, airborne and space-based remote-sensing technologies are used to oversee areas of activity (e.g., laser vibrometry and biological/chemical spectra). Two, an intelligent robotic collective autonomously redeploys optimizing environmental parameter measurements. Three, high bandwidth optical communication pathways to these same remote platforms provide enhanced imagery.

In this proposed scenario, mesoscopic-scale mobile robotic warfighters carrying specialized sensor packages equipped with miniaturized optical reflectance modulators could be infiltrated to suspected proliferation sites or trip-wire locations, interdiction chokepoints or cease-fire boundaries. Data acquisition between a distant mothership or human operative consists of positionally registered and interactively monitored remote transponders using a wide-bandwidth, atmospherically compensated laser communication protocol. To improve robustness of the intelligence gathering process, the robotic agents themselves could be endowed with rudimentary learning ability for collaborative and organized collective behaviors including local remote-sensing coordination (search, evasion, navigation), self-compensation, and adaptive reconfiguration for global optimization of a mapping signature (e.g., signal-to-noise ratio for anthrax. TNT, etc.). Comprehensive representation of the tactical environment in denied areas using an inter-netted architecture of modular war-fighters which possess redundancy overlapping mission capabilities and a degree of decision-making autonomy will significantly enhance operational functionality in dynamic scenarios subject to hazard uncertainties, imprecise information of competing constraints. By creating fault tolerance and improving response-time to active or passive threats without information bottlenecking, and intelligent control system which tasks low-level behaviors in coordinated cooperative fashion can improve the performance of distributed surveillance systems, particularly in complex, information-dense clutter backgrounds such as hostile urban battle-space. When combined with next-generation enabling technologies for ground-based measurement and a communication protocol to support multi-robot connectivity and sensor data-sharing, this approach will form the basis for a new paradigm to remotely exfiltrate critical data with high spacial resolution and situational awareness from previously undetectable targets such as underground structures and migrating effluents or CBW plumes. Areas of specific concern to be addressed by this approach would likely include suspected NBC proliferation sites, underground WMD storage/production facilities in violation of arms-control agreements, terrorist staging and training centers. and clandestine deployment sites for impending military incursions.

Solution Implementation. Implementation of the above multi-agent system combines physics-based N-particle models, artificial intelligent algorithms and global optimization techniques, and sensor R&D.

The interactions and collective effects of large particle ensembles is the study of physics-based models. Physical solutions with strong theoretical underpinnings integrate particle-particle interactions over the entire ensemble. Particle (or robot) attributes, such as charge, mass, or spin, can be linked to macroscopic physical states through known force laws, such as electromagnetism and gravity. The introduction of additional attributes represented by various neural network topologies expands and enhances the autonomy of each robot and the swarm's collective response optimized by genetic algorithms to adapt to unexpected threats or opportunities. As a result, the actual physical motion and decision making attributes can be studied and generated from a superposition of real and fictitious forces generated by system decision-making neural processes.

In figure 1, a block diagram represents the intelligent inter-robot connectivity of the swarm within the collective framework of physics-based models. After a mission statement has been outlined, different required activities are linked to environmental conditions, physical abilities (e.g., robotic platforms), collective behavior (e.g., obstacle avoidance or remote-sensing), and decision-making processes. Accomplishing or dealing with and other factors is realized by modifying and controlling the physical ensemble

DISCLAIMER

DISCLAIMER

An Intelligent Swarm

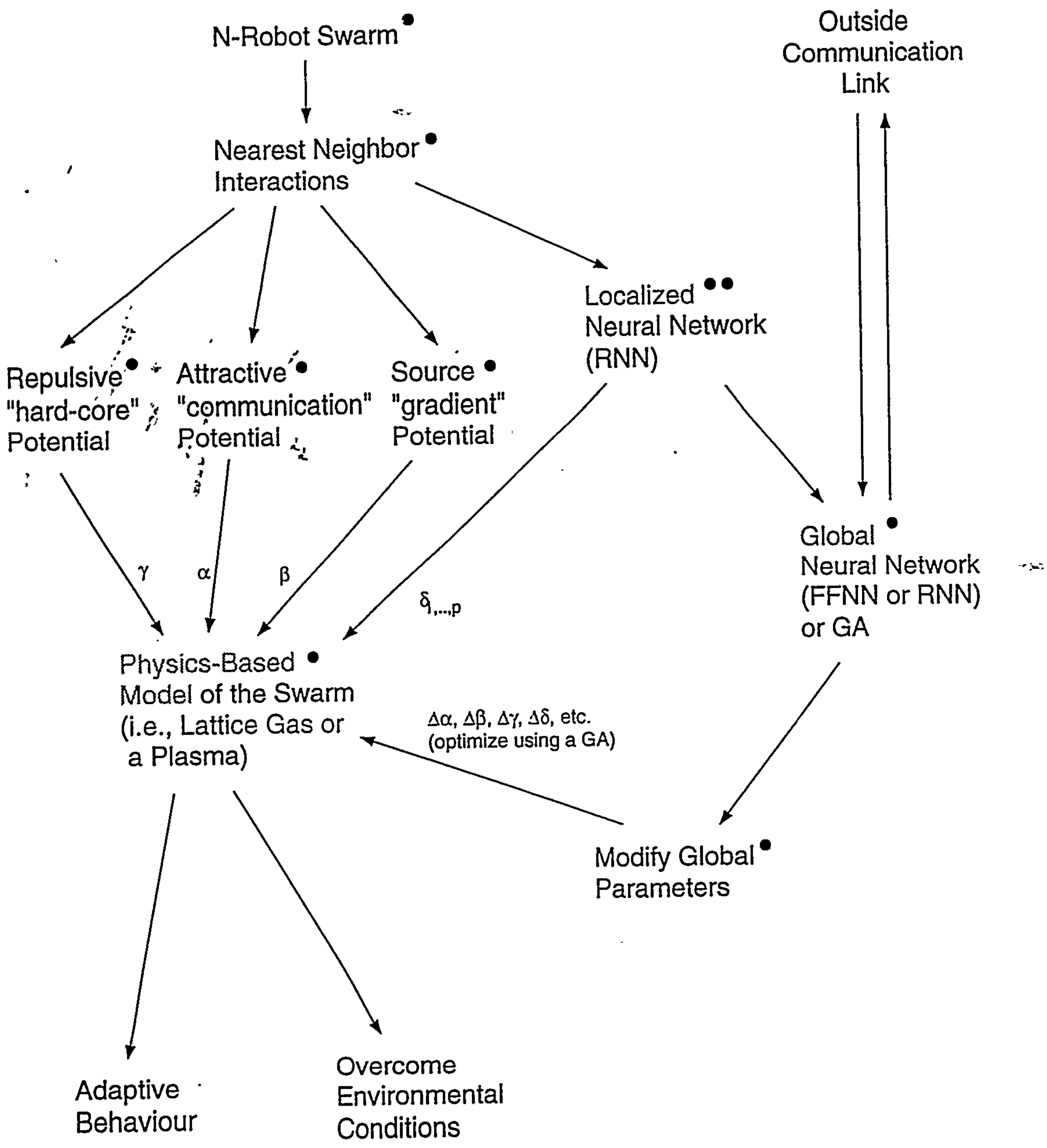

Figure 2. Block or Flow Diagram Representing An Autonomous, Intelligent Swarm Based on a Physics Models.

(dynamics) of the agents. Environmental responses (obstacle avoidance) and information sensing all require a level of intelligence (conscientiousness) at both a local (effecting subset of swarm) and a global (same correlation length as the collective) level. When and at what level one effect dominates (in time) over others (series of tasks) can be determined through global optimization algorithms. The end result is the most efficient method needed to successfully accomplish the mission.

The outline of this paper follows. Section 2, oversight monitory, which determines areas of further study, is briefly overviewed. Sections 3 and 4, a physics-based model of intelligent collective sensors is outlined and their application to ground-penetrating radar (GPR) and bio/chemical remediation. Section 5, optical communication tests are discussed. Conclusions and a brief status of our R&D effect is given in the final section.

2 REMOTE DETECTION OVERSIGHT

Underground activity and chemical/biological profiles of trace elements can be detected. In many cases, exact location or species component differentiation remains difficult requiring further deployment of intelligent sensor array can provide enhanced image and spectral data. The former can be done implementing remote detection oversight methodologies. One such technique is laser vibrometry.

The remote acquisition of high-density, full-field ground flexural mosaics which are discernible from natural background patterns and which can be correlated with characteristic transient ground disturbances in frequency, amplitude, and phase will provide the basis for identifying potential buried structures previously undetected by conventional reconnaissance overflight. MOdal vibrational analysis of the resulting surface deformations in conjunction with geospatial registration, terrain overlays, coherent change detection, and joint time-frequency pattern recognition algorithms will facilitate the reconstruction of approximate source locations as a precursor to selective deployment of autonomous tactical ground-based sensor arrays. Physical sensors positioned on the ground in the vicinity of suspected underground facilities offer improved resolution over remote vibrometry for data exfiltration, but require advanced queuing or intelligence guidance of delineating deployment areas. Space-based or airborne laser vibrometry will play a primary role in performing look-down surveillance over broad operational areas for initial discrimination of threats and areas of interest warranting further scrutiny. Experimental research establishes the viability of an OPA based self-referencing laser speckle shearing interferometer as a sensitive means to detect surface vibrations, even in the presence of an intervening scattering layer. The instrumental sensitivity to surface displacements overlaps with the predicted range for vibrations due to heavy machinery operated in an underground structure. The OPA technology can be integrated with a standard LIDAR platform and is compatible with active multi-spectra sources [1].

3 AN INTELLIGENT, ADAPTIVE MULTI-AGENT MODEL

The decision-making process of our multi-agent model (swarm of robots) is represented by the flow diagram in figure 1. At the center of this model is the many-body particle physics model which realizes the robots' motion. Additional forces are added as a result of a genetically-trained neural network activity analyzing sensor readings sampling environmental conditions or signature events. Autonomous and potentially complex collective behavior can be achieved by optimizing the physical parameters within the model. Genetic algorithms globally optimize these parameters, such as the potential strengths, the robots' attributes, the function form of the potentials, heterogeneity, and many others, according to mission specific goals.

3.1 Physics-Based Models

Nature appears to be governed by only four fundamental forces : gravitational, electromagnetic, weak, and strong. Associated with each of these forces is a universal coupling constant and a "functional form" dependent on the attributes of the particles involved, such as mass, spin, electric, "weak", and color charges. A combination of these forces bind the atom and its nucleus together, form planets and galaxies, and determine plasmas and gases. Cross-sectional measurements link the functional form of the forces to a particle's attributes. It is through various statistical means (i.e., partitions functions, mean field theories, etc.) that the macroscopic and dynamical state of an N-body system is determined.

Additional forces applied at different space-time points as a result of sensor information introduces controlled, complex behaviors. Forces such as attractive, repulsive, and gradient forces require a minimal amount of hardware but would be no smarter than a gas or plasma. Additional "pseudo-forces" incorporate local, nearest-neighbor interactions associated with a robot's attributes, "pseudo-charges". Realizing a robot's brain by a set of neural network topologies genetically trained to decipher environmental conditions defines a robot's pseudo-charges. It is the superposition of these attribute-related forces that builds a macroscopic model from nearest-neighbor interactions. Two N-body physics models best suited to simulate swarm behavior are lattice gases (LG and LG automata) and Particle-In-Cell (PIC) codes (e.g., plasma physics).

3.1.1 Lattice Gas Methods

A lattice gas[2] is a collection of particles whose positions take on the interconnecting points of a square, triangular, hexagonal (or other topological) lattice. Any one lattice site can allow only a single particle to reside on it. If the kinetic energy of the particles are negligible and a simple, constant nearest-neighbor potential is introduced, the partition function for such an ensemble follow that of an Ising model. Such a partition function is theoretically well understood. Therefore, the thermodynamic states of the gas can be derived, such as the volume, pressure, temperature or internal energy, and density, and linked to those of the swarm, such as communication length, sensor range, cohesiveness, and speed. By redefining collision rules according to force interactions, automata techniques are used to model and simulate particle dynamics[3]. Implementing the correct lattice configuration and collision rules lead to the macroscopic Navier-Stokes equations (flow dynamical equations) in both 2- and 3-dimensions[4]. Leveraging these models realize robotic systems by endowing the particles with intelligence (attributes) and training them to follow the physics model.

At every time step within the algorithm, the particle system evolves by applying both propagation and collision operators. The propagation operator moves each robot along a single lattice edge dependent on the applied vector force. The collision operator (collision rules), defined by the interaction potentials, determines which lattice edge the particle prefers. These potentials controlling the state of the swarm include a repulsive, an attractive, and a gradient (source) field. The functional form of these fields can vary, resulting in different state equations. In this paper, the functional forms of the potentials are $F_{repul}(r) = \frac{1}{r^2}$ for the repulsive force, $F_{attract}(r) = r$ for the attractive force, and $F_{src}(r) = \frac{\partial}{\partial r}\mathrm{Signal}(r) \approx \frac{\Delta \mathrm{signal}}{\Delta r}$ for the source force. Each of these forces interact with their line-of-sight (LOS) nearest-neighbors. Such an interaction range can be realized and measured passively by applying IR or sonar detector responses, or the fusion of both. Each robot determines the forces acting on it according to

$$F(r) = \alpha \cdot F_{attract} + \beta \cdot F_{src} + \gamma \cdot F_{repul} + \sum_i (\delta_i \cdot F^{(pseudo)}{}_i) .$$

Optimizing the coupling strength parameters α, β, and γ (and eventually the function forms) allows the swarm to reconfigure, adapting to the environment it senses. Leveraging off this methodology and the current research into various interaction rules, the swarm's state can be taught to remain within a stable phase-space through the introduction of the theoretical physical equations.

3.1.2 Plasma Physics Methods

Plasma physics[5] deals with the collective effects of a system of electromagnetic fields and of particles, such as conducting liquid or gas. Particle dynamics, conduction, occurs when the charged particles move under the action of the applied fields. Due to this dynamical system, the mass motion of the particles couples with the system and the fields. Biological systems also contain such effects. A flock[6] of interacting individuals or birds must not only communicate with on another but deal with the wake of the entire group. Simulating self-consistent aerodynamic forces is a strength of realized by numerical techniques developed through plasma physics models. Included within each cell are nearest-neighbor interactions. Two examples of which are the repulsive and attractive forces that prevents particle collisions and clusters elements around center-of-mass regions, giving the swarm the ability to divide. Because these forces are of the form r^{-1} and r^{-2} (e.g., electrostatic and gravitational interaction types), incorporating these functional forms into the theoretical structure of multi-particle systems is well understood. As a result, stable and robust behavior is maintained by training the robot's intelligence relation to the derived macroscopic plasma equations.

To compute the long-range correlations in a plasma requires a summation of the forces between all particles, which is of $O(n^2)$. Particle-in-cell (PIC)[7-10] codes break up the physical space into a mesh or cells. The particles in each cell determine the local charge density, from which the potential fields at the mesh corners are approximated implementing Poisson's equation. In effect, an average smeared charge simulates the overall (long range) particle field of the plasma. Simulations can occur with speeds of O(n), allowing many simulations to run in real-time. The stability of these algorithms are well documented, using statistical mechanical methods to determine how mesh size, time scale, particle density, and energy conservation influence performance (stability and consistency).

3.2 Artificial Intelligence

Artificially intelligent algorithms realize additional particle (robotic) attributes. Therefore, the robot's "brains" consist of genetically-trained neural networks. Neural networks[11,12] analyze and interpret the robot's sensor values giving it a certain level of consciousness by sensing, measuring, imaging, assessing, and reacting to its surroundings or a threat. The superposition of these "smart-" or "pseudo-" forces (strengths δ_i) and the collective forces (strengths α, β, and γ) of the physics-based models give the swarm the flexibility and the ability to respond rapidly and to optimally readjust in order to fulfill its mission statement (i.e., swarm theory).

Inspired by the field of neuroscience, artificial neural networks models brain and/or nervous system activity. The basic processing unit is the neuron. A neuron consists of a stoma or base, called a neurode, and many interconnecting synapses, or connections, between other neurons (via its dentrites and axon). Associated with each neurode of a neural network is an activation function. The form of which is modeled by a squashing function, a nonlinear function which remains at a constant activation once beyond a threshold value, remains un-activated below a threshold, and has some function form linking these two activation states ("on" and "off"). The input into a neurode is the superposition of many other neurode output activation values weighted by individual synaptic connections. Thus, a neurode's output activation depends on the weighted sum of previous connected neurode activity and the form of its activation function. The architecture or structure of the neural network is defined by the inter-connectivity of its neurodes, the form of the activation function, and the values of its weights. Architectures which only interconnect between successive layers in the same direction are called feedforward neural networks (FFNNs). If each neurode in one layer is connected to each neurode in the following layer, it is called a fully-connected FFNN. Architectures with connections that feedback to previous layers, called recurrences, are called recurrent neural networks (RNNs). Different feedback or recurrent topologies form different types of RNN (e.g., Elman and Jordan).

The process by which the weights of a neural network are determined is called training[1]. The train-

1. in the strictest sense this is not completely accurate, but this is how it will be defined in the context of this paper.

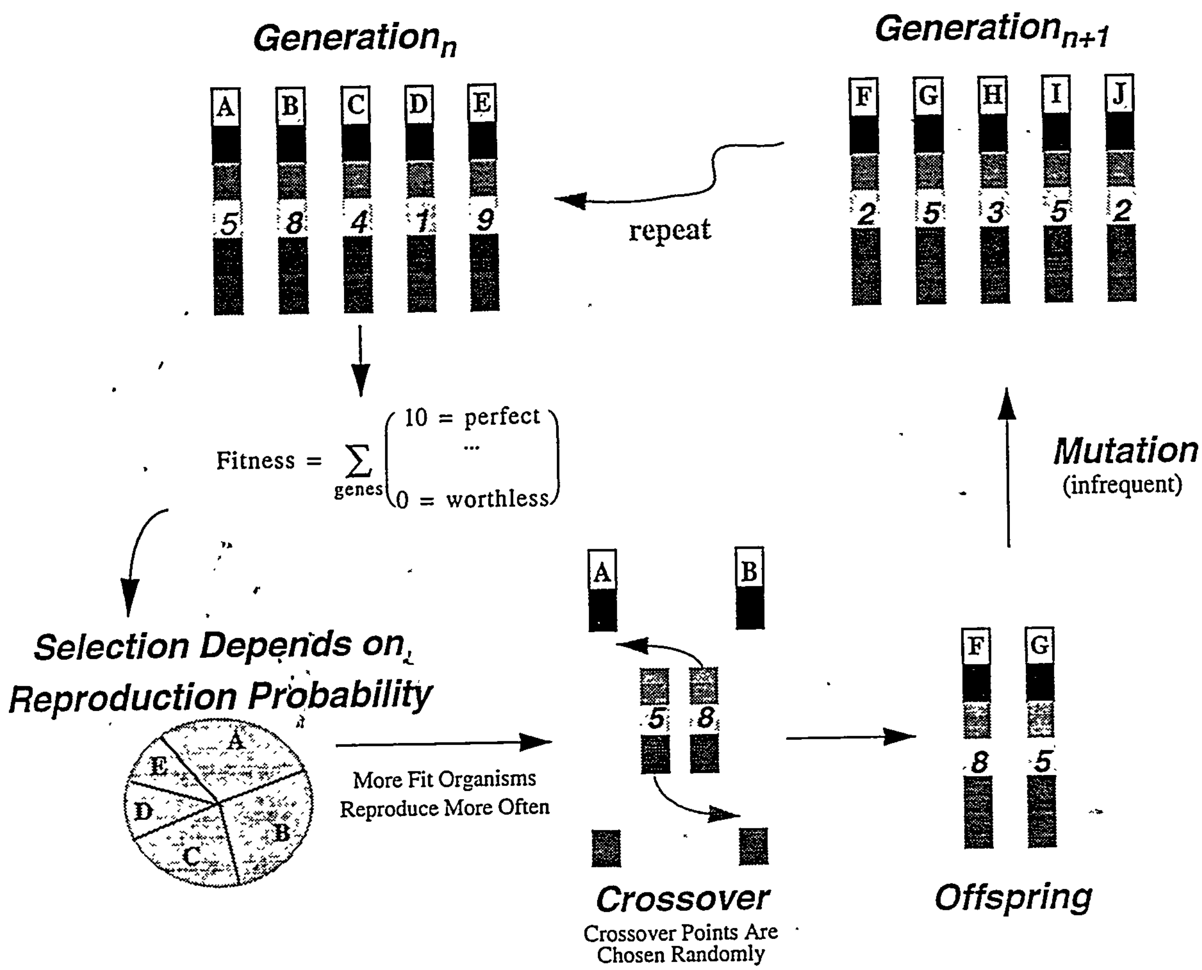

Figure 2. Genetic algorithm operators.

ing methodology used is supervised learning. Supervised training compares calculated neural network outputs to the values associated with the inputs, called the expected outputs. Determination of the weights depends on the output residuals, the differences between the neural network outputs and the expected outputs. Therefore, training a neural network is an iterative process, pairs of input-expected output pairs are "shown" to a neural network and the weights are optimized to give the smallest residuals. The network learns to correlate (recognize) an input pattern by activating certain outputs. Traditional learning algorithms implement back-propagation or gradient search methods to find an optimal set of weights. However, if the net's objective contains discontinuities or if the initial conditions are far from the best solution, training can get caught within a local minima. Implementation of evolutionary programs, such as genetic algorithms (GAs), resolves many of the above mentioned problems.

Successful implementation of FFNN and RNN architectures has been employed. Recurrent neural networks trained to decipher nearest-neighbor information interprets directional motion from sensor readings by "remembering" past events. Such information can be used to produce gradient maps over the entire swarm, and fused with other sensor information providing detailed information about biological or chemical effluents. Feedforward networks trained to recognize bitmap patterns help determine the extend of an obstacle, its edge, or other features needed to overcome it through adiabatic ensemble transitions.

3.3 Global Optimization

The ability to produce desirable macroscopic, collective swarm behavior from local, nearest-neighbor interactions is a huge multivariate analysis problem. Genetic algorithms[13] are stochastic and based on non-derivative techniques, thus they are less likely to get caught in a local minima. They also span a larger variable phase-space without requiring a smooth, continuous objective, thus more likely to find a global optimal solution for a larger set of objectives.

A genetic algorithm performs three operations onto the elements of a population, e.g., a population of neural networks or swarms. Three operations form the basis of a GA, pictured in figure 2. The first operation is selection. Here, the fitness of each element in the population is calculated according to its fitness function, which represents how well the neural network recognizes the inputs by determining its output residuals. The smaller the output residuals, the higher the fitness for that element in the population. Therefore, selection preferentially chooses high fitness elements. The second operation is crossover (e.g., mating). Here, selected elements share sequences of genetic material. In single-point crossover, a common point is chosen along the genetic code (e.g., weights of neural network) of two selected elements, called the parents. Sequences of genes are exchanged about this point. The result is a population of offspring which contains pieces of its parent's solution space. The third operation is mutation. To prevent the population from evolving toward and remaining within a local minima, mutation continually adds new random values (i.e., diversity) into the population. As a result, a larger parameter (weight) phase-space is continually spanned for a global optimum. Like the back-propagation method, a GA is iterative, where each iteration is called a generation. By showing the neural network many input-output pairs over many generations, the population converges to an optimal solution and is considered to have been successfully trained.

Autonomous behavior allows the swarm to adapt. One such example is the ability to avoid obstacles while searching or tracking a source. Simulations implementing nearest-neighbor interactions reveal that rather mundane conditions can cause a swarm to become unstable (e.g., break apart). By allowing a robot's potential strength parameters (e.g., α, β, γ) to depend on time and/or space, a genetic algorithm evolves a population of competing swarms determining which set of spatial regions (or time steps) should change its potential fields. Such a technique greatly enhances the swarms ability to overcome the barrier and to continue to follow the propagating plume. Current work incorporates intelligent, neural network induced potentials (e.g., δ_i) which further improves the swarms performance.

4 APPLICATIONS

The application domain for an adaptive array of sensors or an intelligent multi-agent system is large and permeates through our technology base. Three currently relevant areas of emerging threats include bio/chemical terrorism or warfare, nuclear and biological weapons research and its concealment, and ballistic missile defence against these weapons. Three missions scenarios include ground-penetrating radar (prevention), destruction (remediation), and interception (ballistic missile defence). The former two will be covered in the subsections below.

4.1 Ground-Penetrating Radar (GPR)

Detection of deeply buried underground structures in cluttered terrain or urban environments with unknown geological strata is very difficult to accomplish surreptitiously without recourse to indirect detection methods (e.g., remote vibrometry, secondary signatures) prone to misinterpretation or simple countermeasure. More direct sensing methods such as ground-penetrating backscatter or synthetic aperture radars have offered limited utility for covert applications against subsurface targets because of conflicting practical requirements concerning antenna size scaling versus broadcast frequency content to offset attenuation and dispersion of the electromagnetic pulse in penetrating layered soil media. Because of range losses to the ground surface and impedance mismatch in air, large waveguide antenna geometries with easily detectable microwave emission signatures are required from airborne platforms.

An alternative approach known as a fully adaptive phased array radar, despite many theoretical advantages, has been plagued by the added complexity and longer convergence times that accompany a control loop involving many degrees of freedom. An example of the new type of cooperative remote-sensing and synchronization problems which can be addressed with a distributed hierarchical architecture of mobile robots operating cooperatively at the local level subject to global optimization criteria is a phased impulse radar aperture in denied territory using an intelligent, self-organizing robotic collective of remotely activated rf pulsers. Each basic radiating element of the distributed grid will consist of an omni-directional stripline dipole antenna combined with a compact optically triggered photoconductive semi-conductor switch (PCSS), transmission line, and time-delay circuit or phase-shifter module. Detection will be accomplished using the same receivers in a time-gated cooperative listening mode following the initial impulse to eliminate multi-path dispersion and clutter echoes. Using intelligent algorithms at both the local (repositions, internal timing) and expert level (image quality, resolution), the assembled array can be iteratively optimized in individual phase (synchronization with broadcast laser pulse), amplitude, and spatial orientation ($\lambda/2$ spacing to avoid grating sidelobes) relative to other nearby sensors to create by electromagnetic superposition a directive illumination pattern with modifiable aperture robustly adaptable to local environmental factors such as soil type, dispersion, and anomalous reflections. Since antenna characteristics are determined primarily by the geometric position of the radiators and their relative amplitude and phase excitation, the outgoing radiation pattern would exhibit controllable sidelobe reduction for minimizing clutter and jamming by external noise sources. Active beam steering and the creation of shaped transfer functions as part of an adaptive control loop to maximize signal-to-noise ratio (SNR) could be used to correct for sensing errors, cross-talk, and accommodate building shadowing or constrained search modes. Therefore, beam manipulation and signal management would be orchestrated locally by sub-arrays. This design concept can be overlaid with other autonomous ground sensor measurements including co-registered range-resolved optical imagery and passive extoreceptive signatures. Ongoing Sandia research has developed optically triggered high-gain GaAs semiconductor switch technology as impulse sources for UWB ground-penetrating radar transmitters[14,15].

Thus, an ultra-wideband, short-pulsed phased-array antenna structure provides hyper-spectral image data (position, time, and frequency) which can potentially enhance structure identification. An intelligent, adaptive phased-array antenna in combination with neural network imaging techniques has the ability to find those optimal pathways that can recognize man-made structures deployed deep within the subterrain.

Simulations study various subterrain cross-sectional profiles (range versus depth of 15 by 15 m). Each robot's directional (endfire) antenna transmits a single 15 cm wavelength monocycle pulse. The target (also receiver for these tests) measures signal amplitude. The GA's variables (e.g., genes) are the robots' positions and their relative phases. A swarm's fitness represents how the subterrain dielectric materials affect signal amplitude. A straight-forward calculation implementing Snell's law and the attenuation coefficient for transmission of electromagnetic waves through igneous rock produces a transcendental equation for the path which is solved using numerical techniques. Therefore, the GA determines the swarm's optimal pathways by modifying robots' positions and phases within a swarm.

Results for three different dielectric profiles are analyzed (optimized using a GA) : a horizontal dielectric layer, a vertical dielectric layer, and a horizontal layer with a hole (a narrow increase in the optical potential). The final simulation considers a hole, a minimal resistant pathway, into a horizontal strata of dielectric material (n=2). As pictured in figure 4, the hole spans a range in x from 5 to 8 m. The evolution of the population's maximum (triangles) and average (diamonds) fitnesses are shown in figure 3, and the optimal GA-produced ray-tracing solution after 5, 25, and 50 generations are also displayed. The results indicate a dichonomy between positional and relative phase convergence, where the first 50 generations position the swarm above the hole and the next 100 generations optimize the relative phases of the transmitter pulses.

4.2 Bio/Chemical Plume Remediation

Detection, identification, and remediation of biological toxins in dispersed plumes generated by

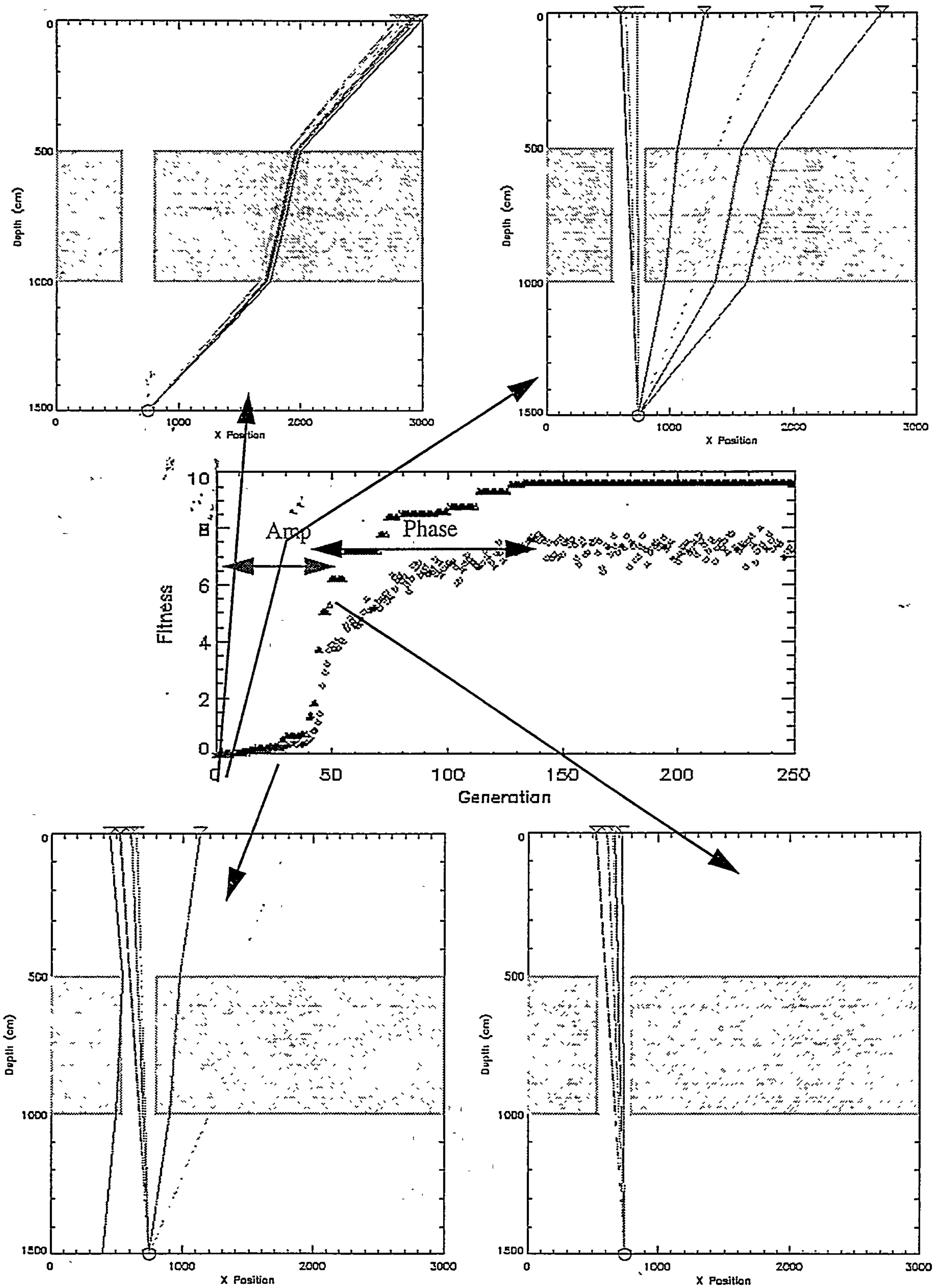

Figure 3. The solution space of the GA after 0, 5, 25, and 50 generations. Center plot displays fitness of optimal phased-array configuration (dark) and average (light) of the population. The latter incorporates mutations. Red region is dominated by superposition of amplitudes. Blue region fine-tunes monocycle phases.

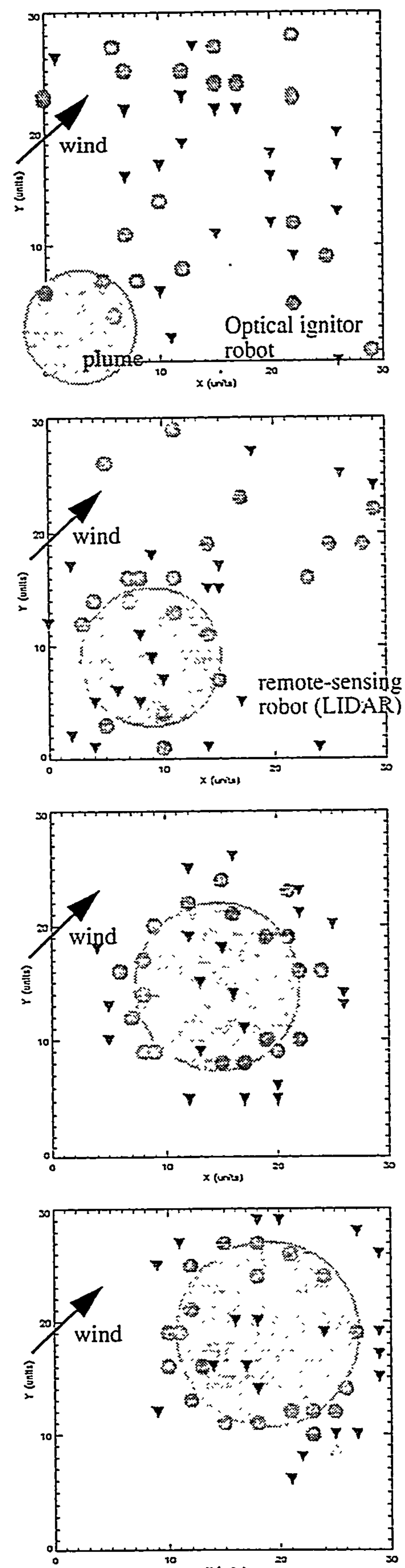

Figure 4. Simulation of a heterogeneous swarm of robots performing the remediation process. Circles are ignitor robots, inverse-triangles are remote-sensing robots. Plume propagates at constant velocity and exponentially expanding and dissipating. A random distribution (top) coalesces onto and propagates beneath swarm (second and third frames). Once condensation occurs (between second and third frames), the inter-connecting pseudo-potentials turn-on, reconfiguring ignitor robots at the plume's edge and remote-sensing robots interior and exterior to the plume.

hostile military forces, terrorists, or illicit proliferation activities pose a challenging security problem. Characteristic spectral signatures are transient in nature due to prevailing wind currents, exhibit significant wavelength diversity, and can be disguised by natural obscurants or interferences which make quantitative chemical recognition by conventional optical measurements problematic. The limited field-of-view of laser sources makes stand-off detection and hazard-interdiction over realistic operational areas impractical for countermeasures. An alternative approach is to spatially map the migrating plume using an intelligent constellation of robots deployed with sensitive agent-specific point sensors.

Envisioned is a distributed sensing architecture in which forward-deployed autonomous elements act initially as an advanced warning trip-wire and then act collectively under a coordinating situational awareness umbrella to optimize interrogation and remediation of the sampling space. First, a robotic swarm positions to secure an area. The robots' platforms would be equipped with a sophisticated optical spectrometer (e.g., enhanced raman spectroscopy) capable of measuring a variety of biological and chemical agents. Second, using advanced intelligent algorithms, the swarm characterizes the plume and coordinates those robots with laser ignition devices that stimulates optical detection of the bio-hazard locally stimulates optical ignition of a munition of UAV-deployable chemical energy source remotely targeted into the plume. Third, the robots tailor their collective behavior to insure destruction of the hazard by controlled combustion from the plume boundary, indiscriminate dispersal by convection and radial shock waves can be avoided. By manipulating the control state vector, it may be possible to actively orchestrate convective flow mechanics and local combustion kinetics so as to permit segregation of the hazardous agent into a prescribed spatial region or to define optimal placement for fuel-air explosives.

The robot's initial configuration should secure sensitive or highly-populated areas, a trip-wire mode. Activating the sensors allows the swarm to coalesce and follow beneath the effluent which is subject to the prevailing wind patterns. By minimizing the communication overhead and only requiring obstacle detection sensors to maintain the swarm's cohesiveness and orchestrate its movements, the swarm's response time is maximal. Two "flavors" (types) of robots -- ignitor robots and remote-sensing robots -- must be positioned to monitor and initiate combustion. Realizing the physics-based model for a swarm, the robot positions (i.e., density of states) are controlled by applying two inter-connected pseudo-potential fields. One field is highly-attractive near the edges of the plume, thus attracting the ignitor-flavored robots; and, the second combines a flat and inverse-radial field, thus distributing remote-sensing flavored robots evenly beneath or inside the plume and sparsely (but not zero) beyond the plume's perimeter. Desirable swarm behavioral patterns can be achieved by genetically training (evolutionary algorithms) potential field parameters. Simulations deploying a heterogeneous swarm as outlined above is shown in figure 4.

Current work will allow the swarm to adapt to environmental factors, such as wind-shifts, terrain, and obstacles, and verification procedures, such as self-containment and eradication of pockets of surviving agents. The goal is to develop real-time adaptive techniques that improves the swarm's autonomy and behavior allowing it to perform within a variety of environments.

5 OPTICAL COMMUNICATIONS

Laser optical communication potentially offers significant advantages for remote coordination and data exfiltration from covert distributed ground-sensing networks. The spatial coherence of laser transmitters offer favorable gain scaling with low probability of intercept, and the relative temporal coherence of the optical carrier can support tremendous information bandwidth without baseband interference or frequency allocation problems. A major weakness limiting the operational utility of nonideal optical communication channels propagating in atmosphere, however, has been adverse effects of extinction (loss), scattering (dispersion), turbulence (degraded coherency), and fade which degrade realizable transmission bandwidth and gain aperture for acceptable bit error rate. We have investigated the use of a previously developed active reflectance imaging technique based on an optical parametric amplifier (OPA) receiver to enhance detector sensitivity and error rate performance for unguided digital communication links affected by cloud-like conditions. Using a kilohertz repetition rate femtosecond laser system operating at eyesafe wavelengths, we have evaluated the role of signal-spontaneous OPA beat noise (s-ASE) on amplified signal, noise figure, and channel sampling capacity for various binary modulation formats in both direct and coherent detection modes to establish fundamental response limitations as a function of turbidity.

The optical communication and laser vibrometry designs are synergistic requiring a single experimental platform. In figure 5, an experimental block diagram shows signal amplification and modulation in preparation for transmission, scattering material, and an OPA adaptive receiver reconstructing the original data stream. Binary data is first amplified by an OPA (120 fs widths), modulated by a carrier, and transmitter through an attenuator (e.g., vapor). A type I OPA receiver samples the destorted (reflected) pulse at synchronized intervals, produced time sensitive data for vibrometry. A type II OPA acts like an "optical phased-locked loop", adapting to the pulsed signal rate. A photodiode and threshold (discriminator) recovers the original signal. Type I transmission has been successfully completed.

Future work fully realizes the type II and begins to develop multiplexing in time and frequency leading to teraherz bandwidths. An increased bandwidth in combination with fast optical filter techniques allows for pseudo-random encryption methodologies securing data pathways.

6 CONCLUSIONS

The advantages of modeling swarm dynamics with particle simulation codes include: (1) these codes have been benchmarked, (2) they provide an accurate dynamical description of N-body system, (3) the theoretical equations describing the particle ensemble are well developed and tested, (4) the link between

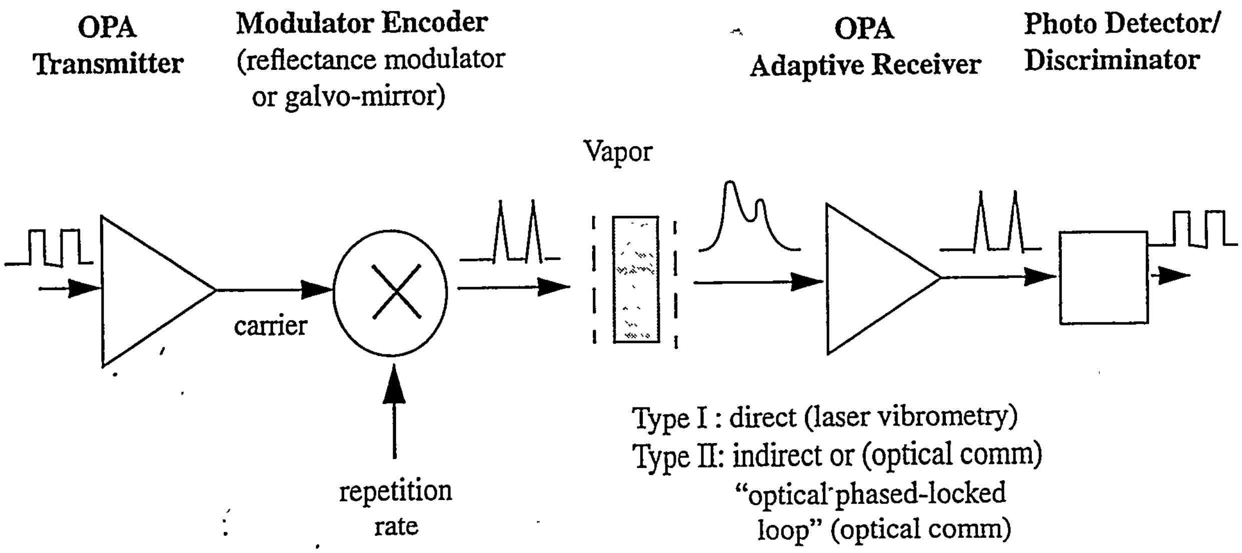

Figure 5. Test setup of an optical communications pathway.

short- and long-range behavior is established, (5) resolves the n^2 computational bottleneck, (6) a methodology exists to include and determine swarm behavior when adding of other features or attributes, and (7) robust training and performance can be built into the framework of the swarm's behavior and tested in real-time. Successful simulations implementing the physics-based model for sensor deployment has been demonstrated for GPR and bio/chemical hazard remediation processes. Global optimization of a phased-array antenna is capable of finding the best imaging pathways through a layered dielectric subterrain to a target. It has also been shown that a heterogeneous swarm can internally reconfigure while characterizing a wind-blown plume demonstrating autonomous execution of the process.

Ground-based deployment can be determined by long-distance remote sensing, i.e., laser vibrometry. Information can be uplinked through obscurants (clouds, canopy) implementing optical communications techniques outlined in figure 5. The instrumental platform can be used for both vibrometry and optical communications.

ACKNOWLEDGEMENTS

Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy under Contract DE-AC04-94AL85000. This work was supported under the LDRD proposal 99-0837.

REFERENCES

[1]
[2] K. Huang, Statistical Mechanics, John Wiley & Sons, (1987)
[3] J. Hardy, O. de Pazzis, Y. Pomeau, Molecular dynamics of a classical lattice gas: Transport properties and time correlation, Physical Review A, Vol 13, No 5, (1976)
[4] U. Frisch, B. Hasslacher, Y. Pomeau, Lattice-Gas Automata for the Navier-Stokes Equation, Physical Review Letters, Vol 56, No 14, (1986)
[5] J. Jackson, Classical Electrodynamics, John Wiley & Sons, (1975)
[6] C. Reynolds, Flocks, Herds, and Schools: A Distributed Behavioral Model, Computer Graphics, Vol 21, No 4, (1987)

[7] C. Birdsall, A. Langdon, Plasma Physics Via Computer Simulation, McGraw-Hill, (1985)
[8] A. Appel, An Efficient Program for Many-Body Simulation, SIAM J. Sci. Stat. Comput., Vol 6, pp. 85-103, (1985)
[9] J. Wagner, J. Poukey, G. Leifeste, BUCKSHOT-MAGIC Comparison for RADLAC Conditioning Cell Parameters, SAND88-1119, (1988)
[10] J. Wagner, M. Mazarakis, BUCKSHOT Simulations of Beam Injection on the Recirculating LINAC, SAND89-0523, (1989)
[11] J. Hertz, A. Krogh, R. Palmer, Introduction to the Theory of Neural Computation, Addison-Wesley Publishing Company, (1991)
[12] S. Haykin, Neural Networks: A Comprehensive Foundation, Maxwell MacMillan, (1994)
[13] D. Goldberg, Genetic Algorithms, Addison-Wesley, (1989)
[14] G. Loubriel, J. Aurand, M. Buttram, F. Zutavern, W. Helgeson, M. O'Malley, High Gain GaAs Photoconductive Semiconductor Switches for Ground Penetrating Radar, Presented at the 1996 22nd International Power Modulator Symposium, Boca Raton, FL (June 1996)
[15] G. Loubriel, M. Buttram, J. Aurand, F. Zutavern, Ground Penetrating Radar Enabled by High Gain GaAs Photoconductive Semiconductor Switches, Ultra-Wideband Short Pulse Electromagnetics 3, Proceedings of the 3rd International Conference, Albuquerque, NM (May 1996)