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Dynamical Behavior of Multi-Robot Systems Using Lattice Gas Automata

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ABSTRACT

Recent attention has been given to the deployment of an adaptable sensor array realized by multi-robotic systems. Our group has been studying the collective behavior of autonomous, multi-agent systems and their applications in the area of remote-sensing and emerging threats. To accomplish such tasks, an interdisciplinary research effort at Sandia National Laboratories are conducting tests in the fields of sensor technology, robotics, and multi-robotic and multi-agents architectures. Our goal is to coordinate a constellation of point sensors that optimizes spatial coverage and multivariate signal analysis using unmanned robotic vehicles (e.g., RATLERs, Robotic All-terrain Lunar Exploration Rover-class vehicles). Overall design methodology is to evolve complex collective behaviors realized through simple interaction (kinetic) physics and artificial intelligence to enable real-time operational responses to emerging threats. This paper focuses on our recent work understanding the dynamics of many-body systems using the physics-based hydrodynamic model of lattice gas automata. Three design features are investigated. One, for single-speed robots, a hexagonal nearest-neighbor interaction topology is necessary to preserve standard hydrodynamic flow. Two, adaptability, defined by the swarm's deformation rate, can be controlled through the hydrodynamic viscosity term, which, in turn, is defined by the local robotic interaction rules. Three, due to the inherent non-linearity of the dynamical equations describing large ensembles, development of stability criteria ensuring convergence to equilibrium states is developed by scaling information flow rates relative to a swarm's hydrodynamic flow rate. An initial test case simulates a swarm of twenty-five robots that maneuvers past an obstacle while following a moving target. A genetic algorithm optimizes applied nearest-neighbor forces in each of five spatial regions distributed over the simulation domain. Armed with knowledge, the swarm adapts by changing state in order to avoid the obstacle. Simulation results are qualitatively similar to lattice gas.

Keywords: Physics-based models, lattice gas automata, hydrodynamics, nearest-neighbor topology, adaptability, stability, genetic algorithms, neuro-fuzzy network.

1. INTRODUCTION

The distribution and control of a point sensor grid mounted on a multi-robotic platform has gained recent interest. To realize such a system requires both robots and their sensors to be simple, small, and inexpensive. Leveraging the high interconnect density, the redundancy of information, and the ability to move endows the system with the intelligence, robustness, and functionality necessary to perform complex remote-sensing applications such as plume mitigation and ground-penetrating radar [30-32]. As the number of robots increases and applications necessitate a heterogeneous profile, the global and internal dynamics of the system become nontrivial. This paper models the kinetic motion of multi-robotic systems using particle physics techniques and develops design criteria in relation to standard hydrodynamic (and electrodynamic) physical laws.

The authors in reference [4] consider the origin of cooperative behavior by asking the following question: "Given a group of robots, an environment, and a task, how should cooperative behavior arise?" Many designs and/or architectures answer various parts afforded by this premise. Designs targeting applications in the manufacturing industry have developed a manufacturing workcell [6] by coordinating materials handling robots with production machines through broadcast communications and a materials transport technique [7] where robots cooperate indirectly through load-balance sensors. Inspired by biological organisms, cellular robotic architectures [10] are built around a decentralized hierarchical system that incorporates local and global communications in its search for pollutants [8] and transport of materials [9]. In the latter, theoretical calculations determine the optimal number of cells (robots) necessary to carry out the task. Other robotic systems based on biological observation pattern their collective behavior after swarms of bees or flocks of birds [21]. Learning mechanisms evolve collective intelligence in motion planning scenarios [11] and communication and information processing

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in dynamical obstacle avoidance [12]. Similarly, tasks involving geometrical formations are encountered, such as circle [14] and line (or path) formation between two points within an unknown environment [15]. From these and many other examples some key features resurface [4]. One is a system infrastructure, which considers parameters such as robot heterogeneity/homogeneity functionality distribution and communication techniques, local versus global. Two is interaction recognition, examples of which include collision avoidance between robots and hazard assessment from the environment. Three is a collective mechanism capable of realizing complex behaviors through simple rules. Four is intelligence, trained or learned, which provides adaptability and flexibility in task or mission execution. This includes information gathering and interpretation that related to reconfiguration (path planning, interaction types, and pattern formation). Five is surety, which assures stability at all levels – a single robot, the full robotic system, and the successful execution of its mission -- and permeates throughout the design methodology. To date, few papers deal with the dynamics and stability associated with large ensembles of robots [5,13]. Our new technique leverages the framework of physics-based models, thus defining features three and five and assigning stipulations on the rest.

Our motivation is to understand multi-robotic systems (swarms) in the context of physics-based N-body particle models, which unites many relevant features: collective motion, internal dynamics, adaptability, and stability. Two models under study are lattice gas automata (LGA) [16-20], the modeling of hydrodynamic behavior seen in gases and liquids, and particle-in-cell (PIC) [22-25] codes, the modeling of electro- and magneto-hydrodynamics found in plasmas [33]. Each model provides the theoretical framework that realizes macroscopic particle behavior according to local (microscopic) interaction physics, significantly reducing the complexity of a single robot. A comprehensive description of the design technique follows (overall design concept see [30-33]). Each robot is endowed with attributes, sensors and communications interpreted by local cooperative learning neural processes that enable real-time operations controlling movements through robotic forces (call pseudo-forces) or AI mechanisms (neural networks, fuzzy logic). Globally operating expert systems monitor collective behavior leveraging the high density of interconnects between each robot's processing unit, thus providing the high-level of information needed to accomplish an overall task, such as reconfiguring to optimize signature signal integrity, communication pathways, and image quality. Evolutionary computation algorithms imprint onto the system the robot's local attributes, the swarm's global properties, and the mission objectives according to the rules set forth by physics-based models.

A case study simulates a multi-robotic system adapting to its environment while performing a task: overcome an obstacle (a wall) while tracking a wind-blown gaseous plume. Some of the design issues include determining an optimal nearest-neighbor topology, optimizing local interactions that initiate global behaviors allowing the robots to maneuver past an obstacle, and assuring stable performance. In section II, the LGA model shows how it can used to understand swarm dynamics. In section III, case study simulations are performed. Two local interaction techniques are considered: the use of forces inspired by electromagnetics and neuro-fuzzy networks. In section IV, results and future work are discussed, and in section V, conclusions are stated.

2. PHYSICS-BASED MODELS

Nonlinear dynamical effects increase as the number of robots increases. Internal stresses induced by environmental influences can create instabilities making the system unpredictable. LGA links key design elements of the multi-robotic system to theoretically derived physical properties of hydrodynamics. Within the framework of statistical mechanics, local (microscopic) interactions result in statistically significant global (macroscopic) behavioral patterns, such as flow (speed), density (size), and viscosity (maneuverability/adaptability. Requiring LGA (swarms) to successfully reproduce the standard hydrodynamic equations of the Navier-Stokes equation sets physical design boundaries that can eliminate instabilities associated with hydrodynamic behavior, such as turbulence created from excessive shear forces.

In the next subsections, LGA is introduced as a viable model for multi-robotic collectives. The next three subsections discuss the theoretical consequences of LGA in system design: nearest-neighbor topology, adaptability, and stability.

2.1. Lattice Gas Automata

Situated on the ground is a lattice structure, typical examples in two dimensions are the square and the hexagon. Each robot propagates with constant speed along the physical links between lattice sites (propagation operator) and interacts changing direction at the lattice nodes (collision operator). In practice, the robots form this imaginary hexagonal structure by first using a compass to normalize the robots' direction and designing a hexagonal sensor array to setup potential fields, to determine direction (lattice edges), and to anticipate nearest-neighbor interactions. Lattice edge length, the robot's mean free path, must be kept relatively large compared to its turning radius (as measured through its fuzzy distance attribute). At each time-step two operators, propagation and collision (interaction), act on the robot ensemble, thus defining the dynamics of the system. Combining the effects from local interaction rules that obey particle (density) and momentum conservation laws and invariance under the underlying lattice group symmetries, global hydrodynamic behavior (Navier-Stokes equation) results [17]. If robots are allowed to move with multiple-speeds, additional conservation laws are required; only single speed robots are considered here. The maintainability of these properties under environmental conditions is the focus of this section.

Next, the form and variables of the kinematic equation are discussed. In order for LGA to be tractable toward understanding swarm dynamics, local robot density functions, defined as the average of the single-particle (single-robot) distribution function, are assumed uncorrelated (molecular chaos approximation). The result is the Boltzmann transport equation [18-20] (derived from the momentum-balance equation).

$$\partial_t(\rho \cdot u_\alpha) = -\partial_\beta \Pi_{\alpha\beta} \qquad (1)$$

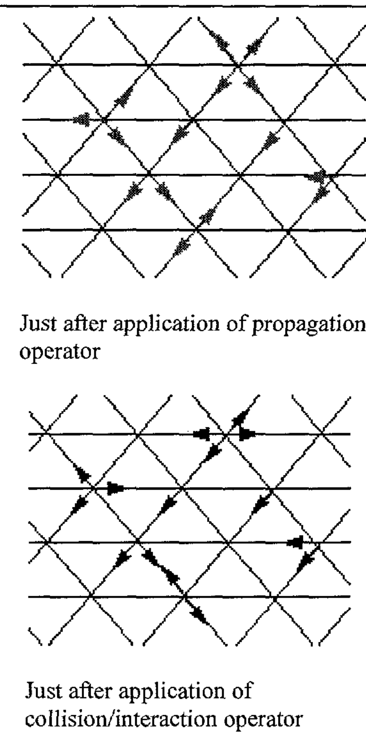


Figure 1. Top, motion of robots along hexagonal lattice edge entering lattice sites. Right, collision or interaction operator, preserving both momentum and particle number.

ρ is the macroscopic (hydrodynamic) density, and u_α is the hydrodynamic velocity. Its lattice gas analogy is $\rho = \sum_i N_i$.

N_i is the averaged single-robot distribution function, and i is an index over the lattice directions. The lattice vectors, and a robot's velocity, are defined by $\vec{c_i}$ or $(c_\alpha)_i$, where Greek indices indicate Cartesian coordinate directions. $\Pi_{\alpha\beta}$, the momentum flux density tensor, is expanded in terms of higher-order ranked tensors representing stresses due to shear and compression.

In the absence of viscosity (shear), the inviscid form of equation 1, Euler equation, describes the equilibrium distribution. Shear stresses develop due to spatial velocity gradients (friction) internal to the swarm. Inclusion of the microscopic collision rules in the momentum flux density tensor produces highly nonlinear hydrodynamic effects. The linearized Boltzmann transport equation is formed by performing a linear approximation to the nonlinear collision operator and keeping only the first order (linear) term. A thermodynamic transformation moves the system from one equilibrium state to another, where a change in the equilibrium state may be due to the environment. Validity of this transformation depends on how fast the perturbed system converges to its new state. Collision/interaction rates, nearest-neighbor communications, and neighbor symmetry topologies are important factors allowing the robotic ensemble to quickly reach equilibrium when adapting to its environment: avoiding obstacles, prevailing wind-patterns, maneuvering within an unknown terrain. If the system converges slowly or produces oscillations, it may become unstable. Training (or evolving) swarm behavior not to exceed these limits assures a level of stability during ground sensor movements.

2.2. Nearest-Neighbor Topology

Robotic interactions can be done indirectly through communications, data transmission through rf broadcast or optical (laser) beams, or directly through sensor measurements, identifying obstacles or recognizing the presence of bio/chemical agents. Implementing IR laser beams provides directionality and eliminates communication interference simplifying robotic platforms (miniaturization) and allowing for asynchronous, parallel operations[1]. Such a technique renders LGA congruent with multi-robotic systems, leading to an optimal nearest-neighbor topological design.

First, a design criterion is established: standard hydrodynamic behavior must be maintained (e.g., Navier-Stokes equation). This basic condition demands all internal tensor stresses as defined by the momentum flux density tensor of rank-4 (shear) and lower must be isotropic, where isotropic requires the tensor to be invariant when acted upon by the discrete symmetry group of the underlying lattice structure. To accomplish this task, let us assume environmental conditions act on the swarm creating various internal stresses that modify its current steady-state configuration. If the parameters defining the macroscopic equilibrium state, swarm's density and momentum, change slowly, the transitional single-robot distributions, N_i, can be approximated by a perturbation series in terms of these same macroscopic variables and their derivatives (Chapman-Enskog expansion) [18,19].

$$\Pi_{\alpha\beta} = f(E_{\alpha\beta} + c_1 E_{\alpha\beta\gamma} + c_2[E_{\alpha\beta\gamma\delta} u_\gamma u_\delta + \sigma \cdot E_{\alpha\beta} |u|^2] + c_3[E_{\alpha\beta\gamma\delta} \partial_\gamma u_\delta + \sigma \cdot E_{\alpha\beta} \vec{\nabla} \cdot \vec{u}]), \quad (3)$$

where

$$E_{\alpha\beta\gamma\delta\ldots} = \sum_i \left(\vec{c}_i\right)_\alpha \left(\vec{c}_i\right)_\beta \cdots \quad (4)$$

must be invariant under the lattice symmetry group. Listed in table 1 is the highest ranked tensor that leaves the swarm's transport equation invariant under the different polyhedral symmetry groups. As a result, the optimal nearest-neighbor topology is six or hexagonal; the robot's single speed and enforcement of momentum conservation excludes the heptagonal lattice structure. It is important to note that introducing multiple speeds may create additional complexity but also reduces the number of neighbors while maintaining an isotropic rank-4 (stress) tensor, a square lattice being an example.

2.3. Adaptability

Adaptability is synonymous with maneuverability. It is defined as the rate-of-deformation of the swarm. Excessive forces created by environmental changes result in shear stresses (internal frictional forces) causing the swarm to become unstable and break apart. The strength of these forces (viscosity) is due to spatial velocity gradients internal to the swarm and depend on the microscopic interactions between neighboring robots. Intelligent manipulation of these interactions or viscosity empowers the swarm to control (optimize) its shape and flow in response to external hazards.

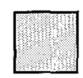
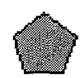
Polynomial Group	Isotropic Tensors
	Rank-3, -5,...
	Rank-4, -6,...
	Rank-5, -7,...
	Rank-7,...

Table 1. Maximum ranked tensor invariant under polynomial group symmetries.

The viscous term in the Boltzmann transport equation depends on the interaction operator. For a hexagonal lattice, one such interaction (collision) between four robots shown at the top of figure 1 is

$$\Delta[N] = \gamma_4 \left(N_1 N_2 \overline{N_3} N_4 N_5 \overline{N_6} - \overline{N_1} N_2 N_3 \overline{N_4} N_5 N_6\right), \quad (5)$$

where

$$\overline{N_i} = 1 - N_i . \quad (6)$$

The non-linearity of these terms complicates the analysis. By keeping shear rates (i.e., swarm reconfiguration rates) small, the collision operator can be linearly approximated about the swarm's equilibrium distribution, N^{eq}. Inserting the eigenvector and eigenvalue solution of this characteristic equation into the Chapman-Enskog expanded form of the Boltzmann transport equation determines the kinematic viscosity of the swarm [19].

$$\nu = \left\{12 N^{eq} \overline{N^{eq}} \left[\gamma_2 \overline{N^{eq}}^2 + 4\gamma_{3A} N^{eq} \overline{N^{eq}} + \gamma_4 {N^{eq}}^2\right]\right\}^{-1} \quad (7)$$

[1] Because of the LGA size, number of particles, spatial and time variations appear uncorrelated. In practice, this may not be true for modest sized multi-robotic systems and may require simulations with a mechanism that builds in asynchronous time evolution.

The viscosity is a function of the average single-robot density and the interaction rules. By expanding and contracting, the swarm can increase or decrease its viscosity which allows it to control its maneuverability; and, by controlling its interactions (communications) between neighboring robots, it can deform which allows it to adapt to its environment. Therefore, when a robot encounters an obstacle it modifies its form and flow by introducing shear forces. Also, its internal time-scale quickens. To maintain a continuous equilibrium transition requires an increased rate of interactions or communications relative to swarm movements, effectively renormalizing the lattice length and time scales relative to the change, the obstacle. Similar considerations occur when tracking wind-blown plumes (sensor-developed flow), terrain topologies (represented by potential field barriers), and internal reorganization. Practical limits must be set to prevent instabilities.

2.4. Stability

A stability analysis qualifies and quantifies perturbations, parameter deviations, preventing convergence toward an equilibrium state. Two considerations in this analysis include the transitional path (transients) between equilibrium distributions and the relative propagation rate of information and the swarm's dynamics.

A slow deformation of the swarm is analogous to performing many infinitesimal transitional rotations between equilibrium states. This series of transitions are due to changes in the swarm's viscosity relative to an obstacle and can be approximated by performing a linear expansion of the interaction matrix. The new form of the Boltzmann transport equation is

$$\partial_t \varepsilon_i \approx \sum_j \Omega_{ij} \varepsilon_j = \sum_j \lambda_j \left(\overrightarrow{v_j}\right)_i . \tag{8}$$

The general solution takes on the form $\varepsilon(t) \approx \varepsilon(0)\, e^{\lambda t}$, where λ is the eigenvalue and represents the rate at which the swarm converges toward an equilibrium state and v_i are the eigenvectors. For a hexagonal lattice the non-zero eigenvalues are [19]

$$\begin{aligned} \lambda_3 &= -3f^2\overline{f} \cdot \left\{ \left[\gamma_2 \overline{f}^2 + 4\gamma_3 f\overline{f} + \gamma_4 f^2\right] - j\frac{4\sqrt{3}}{3}\left[\overline{f}^2\left(\tfrac{1}{2}\gamma_2 - \gamma_{2L}\right) + f^2\left(\tfrac{1}{2}\gamma_4 - \gamma_{4L}\right)\right]\right\} \\ \lambda_5 &= \lambda_3^* \\ \lambda_4 &= -6\gamma_{3S} f^3 \overline{f}^2 \end{aligned} \tag{9}$$

Zero eigenvalues represent macroscopic parameters associated with conservation laws and persist for long times, while non-zero and negative eigenvalues indicate the presence of additional kinematic modes that decay toward at a rate dependent on its magnitude. Also notable are any asymmetric interactions that can produce oscillatory transitions due their non-zero imaginary term for the eigenvalue. Problems arise if these oscillations are not dampened (fast enough) or the internal interaction rate within the swarm is not fast enough to allow it to reach an equilibrium distribution (instabilities in the form a chaotic motion). Another consideration is the elimination of three-robot interactions that creates an additional (spurious) conserved quantity with possibly undesirable effects (e.g., square lattice decouples x- and y-momentum conservation). Simplifying the analysis by requiring all interactions to be symmetric keeps the eigenvalues real and provides an eigenvalue range from –2 to 0, thus assuring stability [18].

A more traditional approach models the swarm as an ongoing computational problem, similar to finite-difference methods or particle-in-cell calculations. By perturbing the density and velocity about an equilibrium flow and setting limits to the (dimensionless) characteristic parameters set by the problem, stable behavior can be maintained. Two important parameters are $C_u = \tau \cdot u_0 / h$ (Courant-Friedrichs-Levy number) and $C_v = \nu \cdot \tau / h^2$, where τ is the travel-time between lattice sites (LGA time step) and h is the distance between lattice sites. The former measures the velocity of the flow in lattice variables, the latter measures their viscosity across the lattice variables. Reference [18] quotes the conservative limit $C_v > q \cdot C_u^2$, where q depends on the specific model. Therefore, stability is achieved when the robots interact (communicate) at a rate faster than their movements (flow). This allows the swarm to convergence when transiting between equilibrium states as it deforms.

To recapitulate, when the swarm adapts to environmental changes, it re-scales (renormalizes) its internal interaction (communication) time-scale relative to the disturbance in order to maintain a transitional equilibrium states. Limiting the rate at which the swarm can deform, defined by such parameters as viscosity and anisotropic flow, prevents instabilities. By implementing the above equations, a swarm can evolve to maintain isotropic tensor interactions and to renormalize interaction rates relative to environmental changes. Such a system can be highly adaptable while assuring stable behavior.

3. SIMULATIONS

The introduction mentions the motivation for deployment of a reconfigurable constellation of unmanned ground vehicles (robots). Initial and ongoing work attempts to evolve a multi-robotic system that can track a moving target, such as a wind-blown plume or effluent, while maneuvering past obstacles lying in its path. The modifiable parameters are the collision rules. Two approaches are considered: electrodynamics, where potential fields or electromagnetic forces determine a robot's direction on the lattice, and neural processes (e.g., neuro-fuzzy network) that perform decision-making movements by fusing neighboring robots' sensor information.

3.1. "Pseudo" Force Method

3.1.1. LGA

A square lattice structure fills in the spatial domain for this simulation. The top left diagram of figure 3 displays the initial position of the swarm, which consists of 25 robots (nRobots=25). A two-dimensional gaussian pulse propagates with constant velocity near the swarm and past a wall, dissipating as it moves. The relative velocity of the plume with respect to a robot's speed is 0.55, about half. Each robot moves according to the angle and magnitude of its vector force [30,31]:

$$F_\alpha = \sum_i^{nn} \left\{ \alpha\left(\vec{X},T\right)\cdot F_\alpha^{attr}\left(|x_i|\right) + \beta\left(\vec{X},T\right)\cdot F_\alpha^{repu}\left(|x_i|\right) + \left[\sum_{pseudo} \gamma_{pseudo}\left(\vec{X},T\right)\cdot F_\alpha^{pseudo}\left(|x_i|\right) \right] \right\}. \quad (10)$$

F_α^{attr} and F_α^{repu} are equal to its neighbor line-of-sight (LOS) distance, r, and inversely proportional to the square of this same distance, r^{-2}, respectively, where $r \le 5$ (interaction/communication range). This prevents the robots from communicating through or over the barrier. F_α^{pseudo} introduces additional fictitious forces. For these tests, a source potential equal to the sensor's spatial derivative, $\approx \Delta s/r$, where Δs is the difference between neighboring sensor measurements, provides the initial steady-state flow of the swarm when tracking the plume. The coefficients α, β, γ, ... amplify forces relative to one other and are functions of the global LGA variables in position and time. Variables with capital letters indicate global quantities relative to the simulation; variables with lower case letters are local quantities measured internal to the swarm. A robot steps along a lattice edge according to the direction of the force when the magnitude of the force exceeds a predefined threshold. To approximate the asynchronicity create by molecular chaos, during each time step a random sequence of robots calculates its interaction force and moves.

3.1.2. Genetic algorithm

Genetic algorithms (GAs) [29] find globally optimal solutions to multivariate problems by applying the rules of evolution: selection, mating, and mutation. A searches for an optimal set of amplification constants over the operational region domain (space and time) of the simulation. The variables (or genes) include the upper and lower diagonal coordinates of the spatial regions and the amplification coefficients, α, β, γ, ..., within those regions. Thus, the genome consists of 35 genes. A population of sixty swarms competes to find an optimal set of parameters that fulfills its mission: avoid the obstacle and maintain contact with the target. After the simulation has proceeded for 70 time steps, the positions of robots are recorded and the fitness of the swarm is calculated according the number of robots maneuvering beyond the wall, x>12 and y>17.

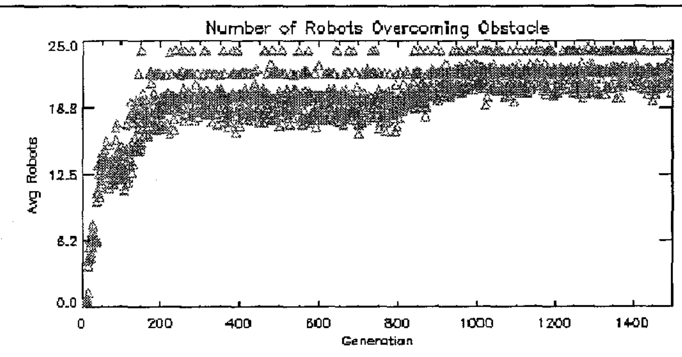


Figure 2. The average number of robots in a swarm of 25 that maneuvers past an obstacle as a function of the genetic algorithm's generation.

$$fitness = \left\{ 0.1 + \frac{\sum_{nC}\left(nRobots - nFollow_{nC}\right)}{nCases} \right\}^{-1} \quad (11)$$

Additional GA parameters include a 10 percent mutation rate, a 90 percent single-point crossover rate, linear fitness scaling, ten ellitists, and an amplification range from 0 to 102.4.

Region	(x_{min},y_{min})	(x_{max},y_{max})	α	β	γ
1	(18,5)	(18,18)	94.8	63.1	5.8
2	(-7,-3)	(5,27)	5.7	5.7	82.7
3	(2,-1)	(12,8)	15.1	14.2	92.2
4	(0,-5)	(9,30)	62.3	86.1	89.1
5	(-4,-4)	(20,20)	10.4	82.4	87.3

Table 2. GA results. The coordinates for each region and the amplification constant for the attractive, repulsive, and spatial sensor gradient forces (see equation 10).

Two operational problems still had to be resolved: the long simulation times and the statistical nature of the simulations. First, development and implementation of a master/slave parallel architecture allows the master to distribute the population of swarms and their LGA simulations among N (20 for these simulations) processors called slaves. After a slave completes its simulation implementing the genetics associated with that particular swarm, it returns a fitness value to the Master. The master performs selection, mating, and mutation operations on the population and redistributes their offspring to the slaves where the next generation's fitness values are calculated. MPI, message-passing-interface, realizes the master/slave architecture. Execution time increases linearly with the number of slaves. Second, the random motion of the robots within a swarm at each time-step even when the initial conditions are identical results in a statistical distribution associated with the fitness, even when a swarm's genetic make-up and initial conditions are identical. Such a simulation is highly desirable but can convergence problems. If the standard deviation is large, crossover becomes ineffective and convergence toward an optimum my not be possible. By running multiple simulations (nCases) for each swarm in the population in succession, the statistical significance of its fitness (~1/√nCases) and the effectiveness of the mating (crossover) operation. An average of nine runs (nCases=9) provides a trade-off between execution time and convergence.

3.1.3. Results

Initially, the wall was removed. Stability was surprisingly bad. Simulations revealed pairs of robots evaporating from the swarm. This effect was exacerbated when the wall was reinserted. Assuming that the anisotropic behavior of stress tensor for a square lattice might be the dominating effect (unproven), a robot's range of motion was also allowed to maneuver diagonally (octagon). Cohesiveness improved substantially. Without the wall, a single region and the coefficients associated with it was enough information for the entire swarm track the plume. Reinsertion of the wall, but with the one region and its coefficients, prevented all robots maneuvering past the wall. Next, the number of regions was increase to five. Figure 3 plots the average number of robots, nFollow, maneuvering past the wall as a function of generation number. The results are listed in table 2, and a simulation run is shown in figure 3.

3.2. Artificial Intelligence Method

Work in the area is in the development stage. A conceptual outline is given.

LGA is based on a simple set of microscopic logistic collision rules that reproduces global hydrodynamic behavior. Pseudo-potential results indicate some level of artificial intelligence is required to recognize an obstacle and to move collectively to avoid it. Instead of binary logistic rules, fuzzy logistic rules in combination with neural networks [26,27] can fuse local information to provide intelligent collective motion that can readily adapt to changes in the environment. Each robot receives information about its neighbor's direction of motion, an obstacle it may have sensed, and the direction of the target. Combined with its own information, the robot decides which direction to move, if any. The first layer of the network contains membership functions for each data type (i.e., three universes of discourse), and the results are fed to a neural network section (layers 2 and 3) which fuse sensor information and provide a decision. Each robot contains the same neuro-fuzzy network [28], and the genetic programming techniques optimize its structure and parameters depending on the success of its mission.

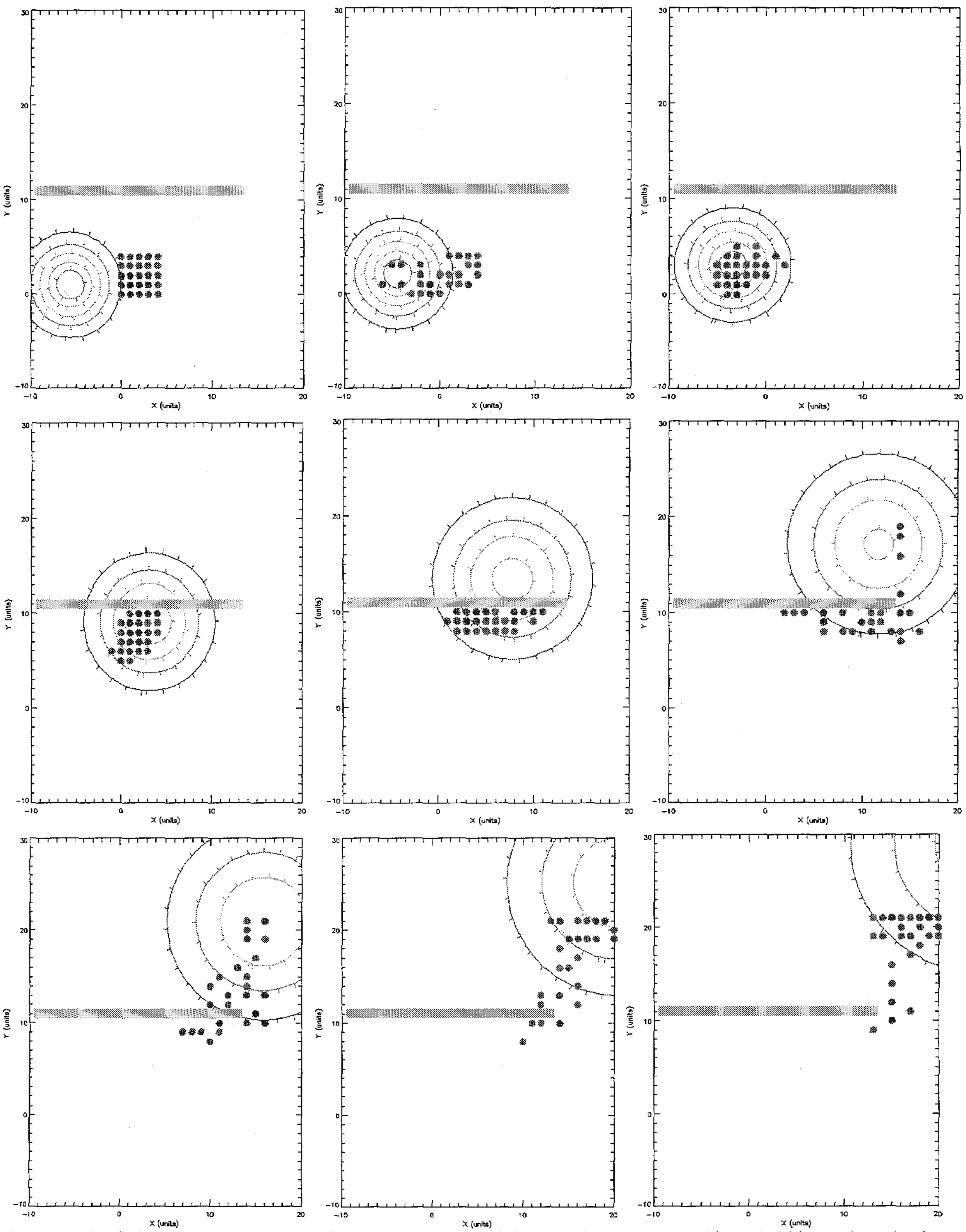


Figure 3. Simulation of a swarm maneuvering past an obstacle while maintaining contact with a wind-blown plume implementing the GA optimized design parameters listed in table 2. From top left to bottom right, on row at a time, the elapsed times are 0.0, 2.6, 5.2, 20.4, 31.2, 40.4, 50.0, 60.4, 69.9.

4. DISCUSSION

Even though twenty-five robots does not constitute a continuum, there are some general correlations that can be made. Both LGA equations and simulation results indicate that a square lattice with four nearest-neighbor interactions is insufficient to maintain cohesive robot flow. Increasing the swarm's kinematic viscosity by expanding the swarm or reducing its density, provides room for the swarm maneuver along and around the obstacle while maintaining interaction rates, effectively rescaling the global LGA parameters (h and τ).

Letting the GA form five regions with differing interaction rules (amplification coefficients for the different forces) provides practical information on the steps needed to avoid the obstacle. The simulation in figure 3 shows that as the swarm approaches the wall its repulsive interactions increase, expanding toward the edge of the obstacle. Near the edge its density dramatically decreases, allowing robots internal to the swarm to maneuver past the wall. The GA balances the interaction potentials so that the shear forces do not cause the robots to evaporate beyond the swarm's boundary. Ultimately, the results from section 2 will be incorporated into the objective function of the GA to help improve performance. Additional simulations testing the LGA hypothesis that rescaling the interaction rates would also improve stability can be accomplished by changing the relative speed of the target to that of the robot's speed or swarm's average speed. Another interesting feature is the number of stationary robots. Stationary particles increase interaction rates and improve convergence (stability) but at the cost of kinematic viscosity. Increasing a robot's force introduces stationary.

The largest deviations between simulation and the theory of LGA are the swarm's boundary due to the finite number of robots and the different forms of the interaction rules. If simulation and theory are to merge, swarms of tens to thousands of robots need to appear like a continuum, Avagadro's number. Current research studying the surface tension between two immiscible fluids provides some insights but for our purposes remains incomplete. By endowing robots with appropriate attributes, the ability to be aware of its position at a boundary of the swarm, it can be made to react as though it is inside a continuum of robots. The hydrodynamic equations in section 2 would provide both the training and the validation necessary. This is not unlike finite-difference time-domain methods where a perfectly matched absorbing boundary layer of material allows a finite scattering domain to appear infinite. Training (recurrent) neural networks implementing standard hexagonal lattice gas automata techniques may resolve this problem.

LGA have shown that simple interaction rules combined with symmetry arguments reproduce hydrodynamics, like the Navier-Stokes equation. It is a powerful framework. Evolutionary techniques have been shown effective at providing optimal system design, by incorporating artificial intelligence into the structure of the robots, giving the swarm the ability to accomplish complex tasks. By incorporating neural network and/or fuzzy logic equations into the robot interaction matrix of equation 5 and 8, theoretical calculations can be developed, enhancing both the swarm's phase-space to maneuver/adapt and its stability.

By endowing the robots with additional attributes (neural topologies, pseudo-potential fields [30-33]) and leveraging this same theoretical framework, intelligence can be studied to see if robotic overhead can be reduced and stability regions can be expanded optimizing adaptability while maintaining surety.

5. CONCLUSIONS

LGA theory relates nearest-neighbor topological information to desirable and predictable swarm dynamics (kinematics). For single-speed particles, a hexagonal distribution of movements and neighbors reproduces standard hydrodynamic behavior. Microscopic robotic interactions are linked to important macroscopic flow parameters, such and density and viscosity. These internal stresses allow the swarm to deform (i.e., change shape), allowing it to adapt to changing environmental conditions. However, nearest-neighbor topology (robots degrees-of-freedom) and rate-of-deformation provide conditions in the form of stability criteria. In general, eigenvalues of the linearized Boltzmann transport equation cannot become positive or imaginary. The latter produces oscillatory transitions between equilibrium states, the former causes the robotic system to diverge from equilibrium.

Simulations show qualitatively that nearest-neighbor topology is an important parameter in the design of multi-robotic systems and that viscosity and rescaling are important when the swarm must maneuver past an obstacle. Deriving and evolving various decision-making collision parameters, such as electrodynamics and hybrid neural topologies, within the LGA framework and during the design stage should provide a high level of robustness (surety).

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REFERENCES

[1] K. S. Evans and Cem Unsal, A Reactive Coordination Scheme for a Many-Robot System, IEEE Transactions on Systems, Man, and Cybernetics B, Vol. 27, No. 4, (1997)

[2] T. Fukuda, Go Iritani, T. Ueyama, and F. Arai, Optimization of Group Behavior on Cellular Robotic System in Dynamic Environment,

[3] T. Fukuda and K. Sekiyama, Communication Reduction with Risk Estimate for Multiple Robotic System, IEEE International Conference on Robotics and Automation, Vol. 2, p2864, (1994)

[4] Y. Uny Cao, A. S. Fukunaga, and A. B. Kahng, Cooperative Mobile Robotics: Antecedents and Directions, Autonomous Robots, Vol. 4, No. 1, p7, (1997)

[5] T. Fikuda and T. Kaga, Distributed Decision Making of Dynamically Reconfigurable Robotic System, Proceeding of the IEEE/RSJ International Conference on Intelligent Robot and Systems, Vol 3., p1604, (1997)

[6] K. L. Doty and R. E. Van Aken, Swarm Robot Materials Handling Paradigm for a Manufacturing Workcell, IEEE International Conference Robotics and Automation, Vol. 1, p778, (1993)

[7] D. J. Stilwell and J. S. Bay, Toward the Development of a Material Transport System Using Swarms of Ant-like Robots, IEEE International Conference on Robotics and Automation, Vol. 1, p766, (1993)

[8] V. Genovese, P. Dario, R. Magni, and L. Odeltti, Self Organizing Behavior and Swarm Intelligence in a Pack of Mobile Miniature Robots in Search of Pollutants, Proceedings of the 1992 IEEE/RSJ International Conference on Intelligent Robots and Systems, p1575, (1992)

[9] Y. Kawauchi, M. Inaba, and T. Fukuda, A Principle of Distributed Decision Making of Cellular Robotic System (CEBOT), IEEE International Conference on Robotics and Automation, Vol. 3, p833, (1993)

[10] T. Fukuda and Y. Kawauchi. Cellular Robotics, p745, Springer-Verlag, (1993)

[11] T. Shibata and T. Fukuda, Coordinate Behavior in Evolutionary Multi-Agent-Robot System, Proceedings of the 1993 IEEE/RSJ International Conference on Intelligent Robots and Systems, p448, (1993)

[12] Y. Arai, T. Fujii, H. Asama, . Kataoka, H. Kaetsu, A. Matsumoto, and I. Endo, Adaptive Behavior Acquisition of Collision Avoidance Among Multiple Autonomous Mobile Robots, Proceeding of the IEEE/RSJ International Conference on Intelligent Robot and Systems, Vol 3., p1762, (1997)

[13] K. Jin, P. Liang, and G. Beni, Stability of Synchronized Distributed Control of Discrete Swarm Structures, IEEE International Conference on Robotics and Automation, Vol. 2, p1033, (1994)

[14] Kube, Ronald C and Zhang, Hong, Collective Robotics: From Social Insects to Robots, Adaptive Behavior, Vol. 2, No. 2, p189

[15] G. Lucarini, M, Varioli, R. Cerutti, and G. Sandini, Cellular Robotics: Simulation and HW Implementation, IEEE International Conference on Robotics and Automation, Vol. 3, p846, (1993)

[16] J. Hardy, O. de Pazzis, and Y. Pomeau, Molecular Dynamics of a Classical Lattice Gas: Transport Properties and Time Correlation, Physical Review A, Vol. 13, No. 5, (1976)

[17] U. Frisch, B. Hasslacher, and Y. Pomeau, Lattice-Gas Automata for the Navier-Stokes Equation, Physical Review Letters, Vol 56, No 14, (1986)

[18] D. H. Rothman and S. Zaleski, Lattice-Gas Cellular Automata, Cambridge University Press, (1997)

[19] S Wolfram, Cellular Automaton Fluids: Basic Theory, Journal of Statistical Physics, Vol. 45, p471, (1986)

[20] G. D. Doolen, Lattice Gas Methods, MIT Press, (1991)

[21] C. Reynolds, Flocks, Herds, and Schools: A Distributed Behavioral Model, Computer Graphics, Vol 21, No 4, (1987)

[22] C. Birdsall and A. Langdon, Plasma Physics Via Computer Simulation, McGraw-Hill, (1985)

[23] A. Appel, An Efficient Program for Many-Body Simulation, SIAM J. Sci. Stat. Comput., Vol 6, pp. 85-103, (1985)

[24] J. Wagner, J. Poukey, and G. Leifeste, BUCKSHOT-MAGIC Comparison for RADLAC Conditioning Cell Parameters, SAND88-1119, (1988)

[25] J. Wagner and M. Mazarakis, BUCKSHOT Simulations of Beam Injection on the Recirculating LINAC, SAND89-0523, (1989)

[26] J. Hertz, A. Krogh, and R. Palmer, Introduction to the Theory of Neural Computation, Addison-Wesley Publishing Company, (1991)

[27] S. Haykin, Neural Networks: A Comprehensive Foundation, Maxwell MacMillan, (1994)

[28] J.-S. R. Jang, C.-T. Sun, and E. Mizutani, Neuro-Fuzzy and Soft Computing, Prentice Hall, (1997)

[29] D. Goldberg, Genetic Algorithms, Addison-Wesley, (1989)
[30] K. M. Stantz, S. M. Cameron, M. W. Trahan, and J. S. Wagner, Optical Communication System for Remote Monitoring and Adaptive Control of Distributed Ground Sensors Exhibiting Collective Intelligence, SAND98-2572, (1998)
[31] K. M. Stantz, R. B. Asher, S. M. Cameron, G. M. Loubriel, R. D. Robinett, M. W. Trahan, and J. S. Wagner, Adpative Remote-Sensing Techniques Implementing Swarms of Mobile Agents, Proceeding from the Fourth Joint Workshop on Standoff Detection for Chemical and Biological Defense, soon to be published, (1998)
[32] S. M. Cameron, G. M. Loubriel, R. D. Robinett III, K. M. Stantz, M. W. Trahan, and J. S. Wagner, Adaptive Remote-Sensing Techniques Implementing Swarms of Mobile Agents, Proceedings of SPIE's 13th Annual International Symposium on Aerospace/Defense Sensing, Simulation, and Controls (AreoSense99), Vol. 3713, (1999)
[33] M. W. Trahan, J. S. Wagner, K. M. Stantz, P. C. Gray, R. Robinett III, Swarms of UAVs and Fighter Aircraft, The International Conference on Nonlinear Problems in Aviation and Aerospace, (April 1998)