Moving Swarm Formations through Obstacle Fields

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***Abstract*— In prior work we established how artificial physics can be used to self-organize swarms of mobile robots into hexagonal formations that move toward a goal. In this paper we extend the framework to moving formations through obstacle fields. We provide important metrics of performance that allow us to (a) compare the utility of different generalized force laws in artificial physics, (b) examine trade-offs between different metrics, and (c) provide a detailed method of comparison for future researchers in this area.**

***Index Terms*— artificial physics, formations, obstacle fields**

I. Introduction

THE focus of our research is to build aggregate sensor systems, specifically, to design rapidly deployable, scalable, adaptive, cost-effective, and robust swarms of autonomous distributed mobile sensing robots. Our objective is to provide a scientific, yet practical, approach to the design and analysis of swarm robotic systems. Target applications for robot swarms include tracing biological/chemical hazards to their source [1].

For such applications each robot forms a grid point for performing computational fluid dynamics (CFD) calculations to follow a chemical/biological plume. Hexagonal grids have been proven to be superior to traditional rectangular grids for numerical solutions of partial differential equations, as needed for CFD. In particular, they are more efficient and effective at handling boundary conditions [2].

It is assumed that robots can sense and affect nearby robots; thus, a key challenge of this project has been how to design "local" control rules. Not only do we want the desired global swarm behavior to emerge from the local interaction between robots (i.e., self-organization), but we also would like there to be some measure of fault-tolerance i.e., the global behavior degrades very gradually if individual robots are damaged. Self-repair is also desirable, in the event of damage. Self-organization, fault-tolerance, and self-repair are precisely those principles exhibited by natural physical systems. Thus, many answers to the problems of distributed control can be found by studying the natural laws of physics.

In prior work we have shown how our *artificial physics* framework can be used to self-organize swarms of mobile robots into hexagonal lattices that move toward a goal [3], [4], [5]. We now extend the framework to include motion through an obstacle field. Our objective is two-fold. Prior research in this area has generally focused either on a small number of robots moving through a large number of obstacles, or a large number of robots moving through a small number of obstacles [6], [7]. However, the more difficult task of moving a large number of robots in formation through a large number of obstacles is generally not addressed. Also, proposed metrics of performance are not complete, ignoring criteria such as the number of collisions between robots and obstacles, the distribution in time of the number of robots that reach the goal, and the connectivity of the formation as it moves. Hence, one objective is to provide a more complete set of metrics from which meaningful comparisons can be made. Second, we will use these metrics, coupled with a more complete experimental methodology, to examine (a) different strategies for performing the task, and (b) trade-offs between different criteria.

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First, we summarize the general artificial physics framework. Second, we summarize our technique for optimizing force law parameters using an evolutionary algorithm (EA). Third, we explain our experimental methodology and performance criteria. Fourth, we compare two different classes of force laws using the performance criteria. We conclude with a discussion of related work and our plans for future work.

II. The Artificial Physics Framework

In our artificial physics (AP) framework, virtual physics forces drive a swarm robotics system to a desired configuration or state. The desired configuration is one that minimizes overall system potential energy, and the system acts as a molecular dynamics ($\vec{F} = m\vec{a}$) simulation.

Each robot has position $\vec{p}$ and velocity $\vec{v}$. We use a discrete-time approximation to the continuous behavior of the robots, with time-step Δt. At each time step, the position of each robot undergoes a perturbation $\Delta\vec{p}$. The perturbation depends on the current velocity, i.e., $\Delta\vec{p} = \vec{v}\Delta t$. The velocity of each robot at each time step also changes by $\Delta\vec{v}$. The change in velocity is controlled by the force on the robot, i.e., $\Delta\vec{v} = \vec{F}\Delta t/m$, where m is the mass of that robot and $\vec{F}$ is the force on that robot. F and v denote the magnitude of vectors $\vec{F}$ and $\vec{v}$. A frictional force is included, for self-stabilization.

From the start, we intended to have our framework map easily to physical hardware, and our model reflects this design philosophy. Having a mass m associated with each robot allows our simulated robots to have momentum. The frictional force allows us to model actual friction, whether it is unavoidable or deliberate, in the real robotic system. With full friction, the robots come to a complete stop between sensor readings and with no friction the robots continue to move as they sense. The time step Δt reflects the amount of time the robots need to perform their sensor readings. If Δt is small, the robots get readings very often, whereas if the time step is large, readings are obtained infrequently. We have also included a parameter F_{max}, which provides a necessary restriction on the acceleration a robot can achieve. Also, a parameter V_{max} restricts the maximum velocity of the robots (and can always be scaled appropriately with Δt to ensure smooth path trajectories).

III. Hexagonal Lattice Sensing Grids

In prior work we have shown how AP can be applied to self-organize swarms of robots into hexagonal lattices [3], while they move toward a goal [4], [5]. In order to accomplish this, robots must be able to sense the range and bearing to nearby robots, as well as the goal location (Figure 1). All movement is controlled via the $\vec{F} = m\vec{a}$ control law.

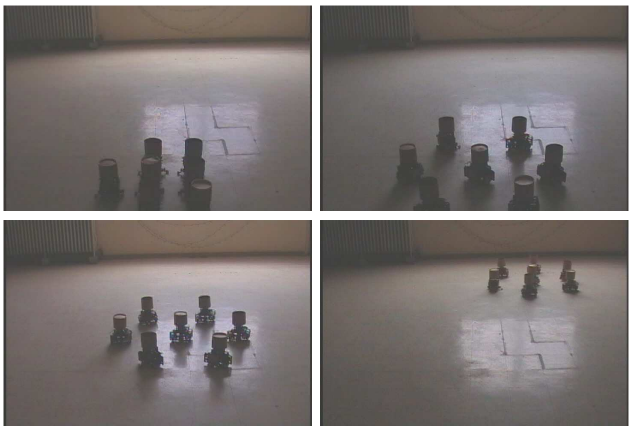

Fig. 1. Seven robots form a hexagon, and move towards a light source.

In this paper we compare two different force laws, in the context of moving formations through obstacle fields. The first has been used in our prior work and is a generalization of the "Newtonian gravitational" force law to include both attraction and repulsion. The force law is:

$$F = \frac{G}{r^p} \tag{1}$$

$F \leq F_{max}$ is the magnitude of the force between two robots, and r is the distance between the two robots. The variable G affects the strength of the force. The variable p is a user-defined power that controls the reduction in strength with distance. The force is repulsive if $r < R$ and attractive if $r > R$. R is the desired separation between that robot and neighboring robots. In order to achieve optimal behavior, the values of G, p, and F_{max} must be determined, as well as the amount of friction. The Newtonian force law generally creates rigid formations that act as solids, even in the presence of sensor and locomotion uncertainty (Figure 1).

In this paper we are also investigating the utility of a second force law, which is a generalization of the Lennard-Jones force law (which models forces between molecules and atoms):

$$F = 24\epsilon \left[\frac{2dR^{12}}{r^{13}} - \frac{cR^6}{r^7} \right] \tag{2}$$

Again, $F \leq F_{max}$ is the magnitude of the force between two robots, and r is the distance between the two robots. The variable ϵ affects the strength of the force, while c and d control the relative balance between the attractive and repulsive components. In order to achieve optimal behavior, the values of ϵ, c, d, and F_{max} must be determined, as well as the amount of friction. Our motivation for trying the LJ force law is that (depending on the parameter settings) it can easily model crystalline solid formations, liquids, and gases.

IV. Optimization using Evolutionary Algorithms

Given generalized force laws, such as the Newtonian force law or Lennard-Jones (LJ), it is necessary to optimize the parameters to achieve the best performance. We achieve this task using an EA. EAs are optimization algorithms inspired by natural evolution. We mutate and recombine a population of candidate solutions (individuals) based on their performance in our environment. One of the major reasons for using this population-based stochastic algorithm is that it quickly generates individuals that have robust performance. Every individual in the population is a vector of real-valued parameters, representing an instantiation of either the Newtonian or LJ force law (depending on the force law being optimized).

In addition to friction, the evolving parameters of the Newtonian force law are:

- G - gravitational constant of robot-robot interactions,
- p - power of the force law for robot-robot interactions,
- F_{max} - maximum force of robot-robot interactions,

and similar 3-tuples for obstacle/goal-robot interactions. The evolving parameters of the LJ force law are:

- ϵ - strength of the robot-robot interactions,
- c - non-negative attractive robot-robot parameter,
- d - non-negative repulsive robot-robot parameter,
- F_{max} - maximum force of robot-robot interactions,

and similar 4-tuples for obstacle/goal-robot interactions.

Offspring are generated using one-point crossover with a crossover rate of 60%. Mutation adds/subtracts an amount drawn from a $N(0, \delta)$ Gaussian distribution. Each parameter has a $1/L$ probability of being mutated. Mutation ensures that parameter values stay within accepted ranges.

Since we are using an EA that minimizes, the performance of an individual is measured as a weighted sum of penalties:

$$Perf = w_1 P_{Collision} + w_2 P_{NoCohesion} + w_3 P_{NotReachGoal}$$

The weighted fitness function consists of three components: a penalty for collisions, a penalty for lack of cohesion, and a penalty for robots not reaching the goal. Since there is no safety zone around the obstacles [7], a penalty is added to the score if the robots collide with obstacles. The cohesion penalty is derived from the fact that in a good hexagonal lattice, interior robots should have six local neighbors. A penalty occurs if a robot has more or less neighbors. If no robot reaches the goal within the time limit, a penalty occurs.

V. Experimental Methodology

A. The Environment

Our 2D simulation world is 900x700, and contains a goal, obstacles and robots. Up to a maximum of 100 robots and 100 static obstacles with one static goal are placed in the environment. The goal is always placed at a random position in the right side of the world, while the robots are initialized in the bottom left area. The obstacles are randomly distributed throughout the environment, but are kept 50 units away from the initial location of the robots, to give the robots the opportunity to first get into formation. Each circular obstacle has a radius R_o of 10, and the square shaped goal is 20x20.

When 100 obstacles are placed in the environment, roughly 5% of the environment is covered by the obstacles (similar to [7]). The desired separation between robots R is 50, and the maximum velocity V_{max} is 20. Figure 2 shows 40 robots navigating through randomly positioned obstacles. The larger circles are obstacles and the square to the right is the goal. Robots can sense other robots within a distance of $1.5R$, and can sense obstacles within a distance of $R_o + 1$ (the minimum sensing distance). The goal can be sensed at any distance.

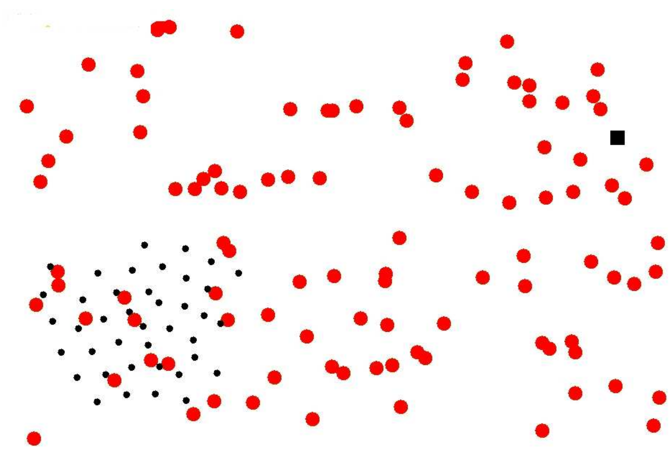

Fig. 2. 40 robots moving to the goal. The larger circles represent obstacles, while the square in the upper right represents the goal.

The simulation tool consists of training and performance modules. The training module is used to evolve parameter sets for either the Newtonian or the LJ force laws. The performance module evaluates the optimized force laws with respect to the following metrics: collisions, connectivity, reachability, and time to goal (to be explained later).

B. EA Optimization

Both Newtonian and LJ force laws were evolved using our training module. The population size was 100 and the EA was run for 100 generations. We first trained over scenarios with 15 robots and 50 obstacles. Each individual (an instance of the force law) was evaluated for 1500 time steps, averaged over 50 random instantiations of the environment. However, the resulting optimized force laws did not scale well to higher numbers of robots and/or obstacles. Training with 100 robots and 100 obstacles was time prohibitive, since the simulation runs in time $O(N^2)$, where N is the total number of robots and obstacles.[1] As a consequence, we settled on a compromise of 40 robots and 90 obstacles.

C. Performance Metrics

After optimization, the best force laws are evaluated with our performance module. The performance module consists of four metrics:

- Collisions: the number of robots colliding with obstacles. We consider such robots to be damaged, but they can still move with the formation.
- Swarm connectivity: the maximum number of robots in the swarm that are connected via a communication path. Two robots are connected if their separation is $\leq$ 1.5R.
- Reachability: the percentage of robots that reach the goal. A robot has reached the goal if it is within $4R$ distance of the goal.
- Time to goal: the amount of time taken by the last robot to reach the goal.

The importance of the collision, connectivity, and time to goal metrics is obvious. We also consider connectivity, since this is an important metric for the quality of a swarm of robots acting as a sensor grid. The connectivity result we will provide is the minimum size of the largest connected swarm, as the swarm moves to the goal. Although each metric provides useful information, a more complete picture arises by considering all.

VI. Results

To measure the performance of the optimized force laws, experiments were carried out with 20 to 100 robots (in increments of 20), and 20 to 100 obstacles (in increments of 20). Each experiment was averaged over 50 runs of different robot, goal and obstacle placements. We first consider the results for the Newtonian force law.

A. Newtonian Force Law

Tables I – IV show the number of collisions, connectivity, reachability, and time to goal results for the optimized Newtonian force law. A '–' entry indicates that the robots did not make it to the goal within the allotted time period.

	Obstacles				
robots	20	40	60	80	100
20	0	0	0	0	0
40	0	0	0	0	0
60	0	0	0	0	0
80	0	1	0	0	1
100	2	2	2	2	3

TABLE I
NUMBER OF ROBOTS THAT COLLIDED WITH OBSTACLES

	Obstacles				
robots	20	40	60	80	100
20	3	3	3	4	5
40	16	15	18	14	21
60	60	60	60	60	60
80	80	80	80	80	80
100	100	100	100	100	100

TABLE II
MINIMUM NUMBER OF ROBOTS THAT REMAIN CONNECTED

It is clear that collisions are not a primary concern. Interestingly, the number of obstacles does not appear to be the important factor here, although the number of robots is.

When there are less than 40 robots, some reach the goal. The time to reach the goal increases as the number of

[1] The simulation compares all pairs of robots to see who they interact with. With the actual robots this occurs in O(1) time.

	Obstacles				
robots	20	40	60	80	100
20	100%	100%	100%	100%	100%
40	83%	77%	63%	49%	37%
60	0%	0%	0%	0%	0%
80	0%	0%	0%	0%	0%
100	0%	0%	0%	0%	0%

TABLE III
PERCENTAGE OF ROBOTS REACHING THE GOAL

	Obstacles				
robots	20	40	60	80	100
20	1180	1190	1410	1490	1490
40	1500	1500	1500	1500	1500
60	–	–	–	–	–
80	–	–	–	–	–
100	–	–	–	–	–

TABLE IV
TIME TO REACH THE GOAL

obstacles increases. However, it is clear that this is achieved by fragmenting the formation into small parts (Table II). When there are more than 40 robots, none reach the goal (within the time period). Instead, the structure remains connected, but the strict rigidity of the structure prevents it from making good progress through the obstacle field. It is clear from these results that training with 40 robots does not yield a Newtonian force law that scales to a larger number of robots.

B. LJ Force Law

Tables V – VIII show the collision, connectivity, reachability, and time to goal results for the optimized LJ force law.

	Obstacles				
robots	20	40	60	80	100
20	0	0	0	0	0
40	0	0	0	0	0
60	0	0	0	0	0
80	0	0	0	1	1
100	1	1	2	4	5

TABLE V
NUMBER OF ROBOTS THAT COLLIDED WITH OBSTACLES

	Obstacles				
robots	20	40	60	80	100
20	8	8	8	8	8
40	20	20	20	21	21
60	34	34	34	35	35
80	49	49	49	49	49
100	64	64	64	64	64

TABLE VI
MINIMUM NUMBER OF ROBOTS THAT REMAIN CONNECTED

Again, it is clear that collisions are not a primary concern. As before, the number of obstacles does not appear to be the important factor here, although the number of robots is. The

	Obstacles				
robots	20	40	60	80	100
20	100%	100%	100%	100%	100%
40	100%	100%	100%	100%	100%
60	100%	100%	100%	100%	100%
80	100%	100%	100%	100%	100%
100	100%	100%	100%	100%	100%

TABLE VII
PERCENTAGE OF ROBOTS REACHING THE GOAL

	Obstacles				
robots	20	40	60	80	100
20	510	520	520	520	530
40	590	600	620	590	600
60	680	680	700	690	690
80	780	790	780	780	780
100	870	870	870	830	870

TABLE VIII
TIME TO REACH THE GOAL

differences in collision results between LJ and the Newtonian force law are statistically insignificant.

However, the other results are quite different. First, all of the robots make it to the goal, in all circumstances. The time to reach the goal increases slowly as the number of obstacles and robots increases (with the number of robots having a larger effect). Finally, swarm connectivity remains reasonably high, ranging from 40% to 64%. Interestingly, swarm connectivity increases as the number of robots increases, and is almost totally unaffected by the number of obstacles. In contrast with the Newtonian force law, the LJ force law (which is trained with 40 robots) scales well with larger numbers of robots. This provides evidence that the LJ force law is a good model for the swarm behavior that we desire.

Observation of the system behavior shows that the formation acts like a viscous fluid, rather than a solid. Although the formation is not rigid, it does tend to retain much of the hexagonal structure. Deformations and rotations of portions of the fluid are temporary manifestations imposed by the obstacles. Hence, the added flexibility of this formation (over that achieved by the Newtonian force law) has a significant impact on behavior. The optimized LJ force law provides low collision rates, very high goal reachability rates within a reasonable period of time, and high swarm connectivity.

VII. RESULTS WITH A SAFETY ZONE

The force laws evolved with the EA produce behavior where the robots skirt the obstacles as closely as possible. This is consistent with the general AP framework, where robots move in a fashion that minimize energy usage. However, as noted above, this can lead to collisions. In this section we examine the trade-offs induced by the addition of a safety zone.

We performed the same experiments as before, for 20 and 100 robots with varying number of obstacles. All obstacles were given a safety zone of size 15, increasing the virtual size of the obstacles. Hence, robots can sense obstacles within a distance of $R_o + 15$. Again, the robots were allowed 1500 time units to reach the goal.

A. Newtonian Force Law

The introduction of the safety zone eliminated all collisions of robots with obstacles, and swarm connectivity results were similar. However, reachability was greatly reduced and the time to reach the goal was increased (Tables IX and X).

	Obstacles				
robots	20	40	60	80	100
20	99%	96%	70%	52%	14%
100	0%	0%	0%	0%	0%

TABLE IX
PERCENTAGE OF ROBOTS REACHING THE GOAL

	Obstacles				
robots	20	40	60	80	100
20	1440	1490	1490	1490	1490
100	–	–	–	–	–

TABLE X
TIME TO REACH THE GOAL

The results were not unexpected. Since the Newtonian force law produces a structure that acts like a solid, the addition of the safety zone make it more difficult for the formation to rotate and counter-rotate (an emergent property of the system) through the obstacles.

B. LJ Force Law

As with the Newtonian force law, the introduction of the safety zone eliminated all collisions of LJ-controlled robots with obstacles, and swarm connectivity results were similar.

	Obstacles				
robots	20	40	60	80	100
20	100%	100%	100%	87%	80%
100	100%	99%	98%	96%	93%

TABLE XI
PERCENTAGE OF ROBOTS REACHING THE GOAL

	Obstacles				
robots	20	40	60	80	100
20	520	520	520	550	580
100	810	890	810	890	990

TABLE XII
TIME TO REACH THE GOAL

Once again, reachability was reduced and the time to reach the goal increased. However, the reduction in performance (see Tables XI and XII) is not nearly as severe as with the Newtonian-controlled robots. The additional flexibility of the viscous fluid works far better.

VIII. Discussion and Elaboration

To further analyze our system, we also collected data concerning the change in the connectivity and the percentage of robots reaching the goal, over time. The resulting graphs are far too numerous to present here, but we present representative examples. All graphs are averaged over 50 independent runs.

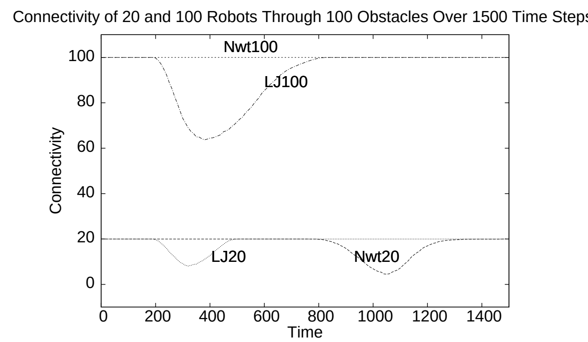

Fig. 3. Change in connectivity over 1500 time steps for 20 and 100 robots through 100 obstacles using Newtonian (Nwt) and LJ force laws

Figure 3 illustrates the change in connectivity of the swarm over time. Two sets of results are presented in this graph. The curves at the top are for 100 robots moving through 100 obstacles. The robots controlled by the Newtonian force law remain fully connected (although, as we know from the prior results, this is because the formation has not succeeded in reaching the goal). However, the swarm connectivity for the LJ-controlled robots drops after 200 time steps, as the formation begins to move through the obstacle field. After 400 time steps, the formation connectivity increases as the robots reach the goal.

The curves at the bottom are for 20 robots moving through 100 obstacles. In this situation the Newtonian-controlled robots arrive at the goal, and the swarm connectivity drops after 800 time steps and then increases after roughly 1050 steps. Because the LJ-controlled formation moves much more quickly, the formation connectivity drops after 200 time steps and then increases after roughly 300 steps. It is interesting to note that the LJ-controlled swarm does not break apart quite as much as the Newtonian-controlled swarm.

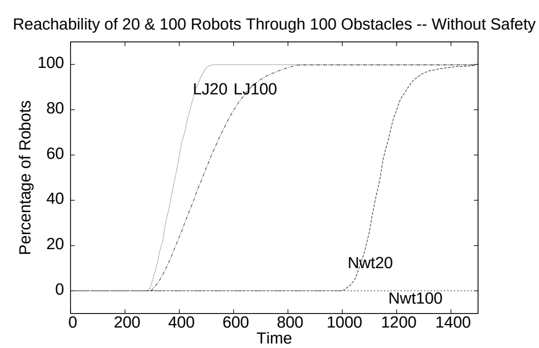

Fig. 4. Percentage of 20 and 100 robots reaching goal through 100 obstacles over 1500 time steps using Newtonian (Nwt) and LJ force laws

Figure 4 shows how the number of robots reaching the goal changes with time. Again, two sets of results are presented, for 20 and 100 robots moving through 100 obstacles. The two left-most curves are for the LJ-controlled robots. Note that, regardless of the number of obstacles, robots start to arrive at the goal at roughly the same time (300 time steps). With 20 robots, they have all arrived at the goal by about 500 time steps. This indicates that all robots arrived at the goal within a 200 time step interval – a relatively narrow band in time. Increasing the number of robots to 100 increases the time interval to only 500 steps.

The other two curves are for the Newtonian-controlled robots. With 20 robots, they start to reach the goal at 1000 time steps, and the interval is approximately 400 time steps. When there are 100 robots, none reach the goal within the allotted time period.

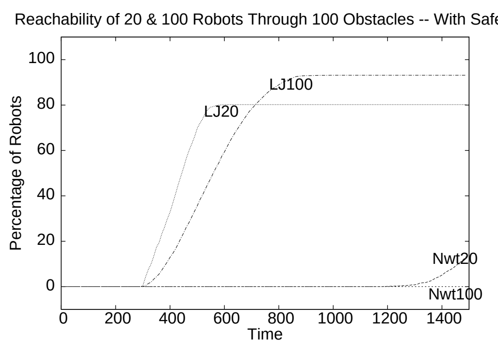

Fig. 5. Percentage of 20 and 100 robots reaching goal through 100 obstacles over 1500 time steps using Newtonian (Nwt) and LJ force laws with a safety zone around obstacles

Figure 5 shows the results of the same experiment, but with the addition of the safety zones around all obstacles. As noted earlier, safety zones remove all collisions. But the impact on reachability is clear. Even with only 20 robots, performance with the Newtonian force law is severely impacted. Performance of the LJ-controlled robots is also impacted, but to a lesser extent. The time interval within which robots arrive at the goal remains relatively unaffected, but the number of robots reaching the goal is definitely compromised.

Figure 6 shows the evolved LJ robot-robot force law. It is strongly repulsive when the distance between robots is less than 50, and weakly attractive when the distance is greater than 50. This weak attractive force provides the "stickiness" that manifests itself as a viscous fluid in the aggregate.

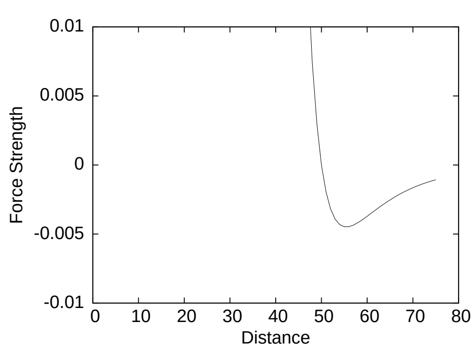

Fig. 6. The evolved LJ force law, which is repulsive when distance is less than 50, and weakly attractive when distance is greater than 50

IX. Related Work

Most of the swarm robotics literature can be subdivided into *swarm intelligence*, *behavior-based*, *rule-based*, *control-theoretic* and *physics-based* techniques. Swarm intelligence techniques are ethologically motivated and have had excellent success with foraging, task allocation, and division of labor problems [8], [9]. Both behavior-based and rule-based systems [10], [6], [11] have proved quite successful in demonstrating a variety of behaviors in a heuristic manner. Behavior-based and rule-based techniques do not make use of potential fields or forces. Instead, they deal directly with velocity vectors and heuristics for changing those vectors (although the term "potential field" is often used in the behavior-based literature, it refers to a field that differs from the strict Newtonian physics definition). Control-theoretic approaches have also been applied effectively (e.g., [12]). Our approach does not make the assumption of having leaders and followers, as in [13], [14].

One of the earliest physics-based techniques is the *potential fields* (PF) approach (e.g., [15]). Most of the PF literature deals with a small number of robots (typically just one) that navigate through a field of obstacles to get to a target location. The environment, rather than the robots, exert forces. Obstacles exert repulsive forces while goals exert attractive forces. Recently, Howard et al. [16] and Vail and Veloso [17] extended PF to include inter-agent repulsive forces – for the purpose of achieving coverage. Although this work was developed independently of AP, it affirms the feasibility of a physics force-based approach. Another physics-based method is the "Engineered Collective" work by Duncan at the University of New Mexico and Robinett at Sandia National Laboratory. Their technique has been applied to search-and-rescue and other related tasks [18]. The *social potential fields* [19] framework is highly related to AP. Reif and Wang [19] rely on a force-law simulation that is similar to our own, allowing different forces between different robots. Their emphasis is on synthesizing desired formations by designing graphs that have a unique PE embedding. We plan to merge this approach with ours.

In the specific context of obstacle avoidance, the most relevant papers are [6], [7] and [10]. Balch [6] examines the situation of four robots moving in formation through an obstacle field with 2% coverage. In [7] he extends this to an obstacle field of 5% coverage, and also investigates the behavior of 32 robots moving around one medium size obstacle. Fredslund and Matarić [10] examine a maximum of eight robots moving around two wall obstacles. To the best of our knowledge, this paper is the first to systematically examine larger numbers of robots and obstacles.

X. Summary

This paper presents a novel extension to our artificial physics framework, with the use of a generalized Lennard-Jones force law. We then summarize how we use evolutionary algorithms to optimize the parameters of the force laws. These force laws were tested within the context of moving robotic swarm formations through obstacle fields to a goal.

In addition, this paper presents novel metrics of performance, namely, the number of robots that collide with obstacles, their connectivity, the number of robots that reach the goal, and the time to the goal. Although each metric provides useful information, a much better picture arises by considering all metrics. Our empirical analysis is methodical, ranging from 20 to 100 robots, and 20 to 100 obstacles.

Our results indicate that LJ-controlled robots have far superior performance to our more “classic” Newtonian-controlled robots. This is because the emergent behavior of the LJ-controlled swarm is to act as a viscous fluid, generally retaining good connectivity while allowing for the deformations necessary to smoothly flow through the obstacle field. Despite being trained with only 40 robots, the emergent behavior scales well to larger numbers of robots. In contrast, the Newtonian-controlled swarm produces more rigid structures that have much more difficulty maneuvering through the obstacles. Furthermore, performance drops dramatically when there are more than 40 robots. Table XIII summarizes the results.

	Newtonian				LJ			
Robots	40	60	80	100	40	60	80	100
Collisions	0	0	1	3	0	0	1	5
Connectivity	21	60	80	100	21	35	49	64
Reachability%	37	0	0	0	100	100	100	100
Time to Goal	1500	-	-	-	600	690	780	870

TABLE XIII

SUMMARY OF RESULTS FOR 100 OBSTACLES, WITH 40 – 100 ROBOTS.

Finally, we use the metrics to consider the trade-offs that occur when a safety zone is introduced around the obstacles. As expected, collisions never occur, but significant reductions in reachability arise. For future work we intend to extend our framework to non-circular and/or moving obstacles. At this point, significant issues arise with respect to the partial observation of obstacles and the presence of traps. We expect to be able to merge methods from Lee et.al. [20] with respect to their handling of partial observations, and the “wall following method” from Borenstein and Koren [21] for avoiding traps.

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