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TOWARD A META-MODEL OF BEHAVIORAL INTERACTION FOR DESIGNING COMPLEX ADAPTIVE SYSTEMS

Winston Chiang
IMPACT Laboratory
Dept. of Aerospace & Mechanical Engineering
University of Southern California
Los Angeles, California 90089-1453
wwchiang@usc.edu

Yan Jin*
IMPACT Laboratory
Dept. of Aerospace & Mechanical Engineering
University of Southern California
Los Angeles, California 90089-1453
yjin@usc.edu (**Corresponding author*)

ABSTRACT

Future complex engineered systems must be adaptable to, and function in, unpredictable situations, such as deep space or ocean explorations, hazardous waste cleanups, and search-and-rescue missions. To increase system adaptability, various multi-agent system approaches have been developed. From a design point of view, a critical question in developing such systems is: *how can system adaptability be designed into complex systems based only on local interactions between (many) simple cells or agents*? Although explicit cooperative methods have been applied to answer this question, their limitation in scaling-up has been recognized. In this paper, we introduce a *meta-interaction model* that can be used as a design approach towards multi-agent complex systems. The approach parameterizes behavioral interactions extended from the Boids swarm intelligence model by introducing dynamical variables into the system. The goal of the meta-interaction model is to provide a mapping for the prediction of collective functionality from local interactions and for the indication of local interactions based on desired functionality. The proposed model is described in detail and a computer simulation based case study of search-and-surround is presented to demonstrate the effectiveness of our proposed approach to designing complex adaptive systems.

INTRODUCTION

In many engineering tasks and mission situations, a designer often cannot predict all possible functional requirements and operational situations that may be needed and encountered by the system being designed. Examples of such application domains include mine sweeping, natural disaster search & rescue, planetary & ocean exploration, and missile flocking. The common theme within these applications is the uncertainty from unforeseen circumstances in either the operation environment or in the required functionality. Environment exploration is a major application of interest because unknown environments such as space planetary surface missions and the deep ocean are beyond the reach of simple human exploration.

To increase system adaptability, various multi-agent system approaches have been proposed, taking advantages of the flexibility of interacting agents. An agent is an entity or computational process that senses the environment and acts on it. Swarm multi-agent systems actively alter their overall structure and inter-relationships, translating into great versatility. This coordination of multiple entities often deals with synchronized complex motion planning thus a major research challenge is to develop methods for agent to act in sync robustly and reliably in response to task and environmental changes.

Common solutions are to use centralized controllers or explicit cooperation algorithms. However, these solutions often do not scale well due to possible delays in the constant exchange of information between sensors, actuators, and the controller. Complex coordination algorithms can often become unmanageable with scale. Furthermore, robustness is hindered from the dependence upon a central controller. Most critically, the centralized control algorithms often cannot deal with unforeseeable circumstances.

Another approach builds upon complex systems theory utilizing self-organization and emergence. These concepts are inspired by nature as engineers strive to take advantage of the robustness and adaptability exhibited in natural systems such as bird flocking, fish schooling, and ant colonies. Self-organization is the idea that individuals will organize into societies based only on local rules and local communication. It is basically large scale organization through limited local interactions of the constituent components. Emergence is the principle that unintuitive or unexpected global patterns will observably materialize from the interactions in the system. Self-organization and emergent behavior have been popular research topics in the complex systems field and many others including biology, thermodynamics, computer science, sociology, and economy [1-7]. Self-organizing systems can accomplish complex tasks with simple individual behavior and components, requiring simple programming and simple architecture of components. This not only decreases the manufacturing expense but eases hardware development and maintenance. Furthermore, self-organizing complex adaptive systems rely on local processes and distributed control, leading to high level theoretical scalability.

The critical advantage of collectively intelligent multi-agent systems is their adaptive ability, i.e., the ability to persist through external and internal changes. The natural world exhibits many biological examples of adaptive systems that robustly adapt to both the external environment and to internal changes. In schools of fish, many fish are capable of moving as a single entity while they disperse to avoid predators and obstacles but quickly gather to reform the school. This collective behavior results from each fish applying a few simple behavior rules of separation and movement. At a deeper micro-level, cells with identical DNA combine to form complex structures. By relying on vast numbers of resource-limited and unreliable cells, cellular systems achieve reliability even in cell death, varying scale, and uncompromising environments.

While the natural systems had the luxury of evolution over millions from bottom up, in our engineering world, achieving bottom-up adaptability by design represents a major challenge to the systems engineering and design research community. Two fundamental issues must be addressed: one is the *analysis problem* of predicting the global emergence from local interactions; and the second is the *design problem* of compiling local rules based on a desired global function. One method to address the issues has been to use empirical approaches to simulate and model the observed responses exhibited in natural systems; however, this relies on trial-and-error and can be difficult to use as an engineering tool. Another method is to implement communication mechanisms that trigger direct responses from individual agents, but this means that individual actions under specific conditions are already pre-specified.

In our research, we propose a cellular self-organizing (CSO) approach to developing complex adaptive systems. In the CSO framework, a system is composed of multiple mechanical (e.g., robotic) cells, which self-organize themselves through individual actions and mutual interactions. To deepen our understanding and provide design methods for the development of CSO systems, in this paper, we introduce a design approach focusing on the relationship between local agent interactions and emergent collective system behavior. More specifically, a parametric approach centered upon interactive behaviors will be used to develop a meta-model of the behavioral model of agent interactions. Once complete, the approach can be used to manage adaptive ability by specifying interaction patterns of agents in a multi-agent system. Furthermore, parameterizing local behaviors provides an opportunity to analyze the relationship between different types of local interactions in addition to the relationship between the local interaction and the collective functionality.

In our proposed CSO systems, each simple mechanical cell or agent usually cannot accomplish much by itself, but many cells organized properly can collectively achieve specified tasks. Global patterns will emerge from only local interactions between the individuals. It is hypothesized that properly designed local rules of self-organization will result in useful emergent collective behaviors and functions and that by utilizing a behavioral approach focusing on interaction between cells, a CSO system of many agents can be designed with collective functionalities. Using the parametric approach provides tunable dynamical variables towards managing collective behavior, leading to various desired global functions.

In the rest of the paper, we first review the related work in the next section. After that a meta-interaction model approach is presented and discussed, followed by a detailed description and discussions of computer simulation based case studies. Future work and concluding remarks are described in the last two sections.

RELATED WORK

Self-organization and emergence has been used to study many natural systems such as chemical pattern formation, traffic jams, termites, and ant social behavior [8-11]. Much research focuses on creating a model that can parallel the natural system in order to understand how the natural system works. Extending such work, many of the observed natural techniques and principals are applied to artificial systems. One common example in mobile robotics is the application of ant-like behaviors such as stigmergy [8, 11].

Reynold’s Boids is a well recognized example of emergence in swarms where the collective complexity results from the local interaction of individual agents [12]. Each agent follows three simple rules of interaction: separation, velocity matching, and flock centering. However, more rules must be added to produce obstacle avoidance and goal seeking for true system functionality [12]. Mataric developed learning in group environments by using a set of basic behaviors abstracted from the Boids framework [13]. The behaviors served as building blocks for synthesizing and analyzing learning group behaviors. Couzin's group also uses a method extended from the Boids framework in order to study movements in real collective animal systems [14]. By using a parametric matching approach, they try to find the true characterization of collective motion in animal groups.

One of the challenges in using self-organizing approaches is to take a global goal and then generate the local rules of interaction. Stoy and Nagpal introduced a distributed approach where information is communicated in the form of directional gradients, which direct elements towards empty locations as defined by a CAD represented desired shape [15, 16]. In another approach, Nagpal had developed a language for instructing a sheet of identically-programmed agents to assemble themselves into a predetermined global shape [17]. The process of construction is sequenced, triggered, and communicated through the cells of the sheet by means of a gradient message. Both of these approaches constrain the system to preconceived structures dependent upon human understanding and creativity, and there is also no direct translation towards functionality.

Another distributed communication method for task execution is the bio-inspired Digital Hormone Model, DHM [18]. With DHM, each component of a swarm can communicate via hormones and execute local actions via receptors. These actions are based not only on the received hormone, but also on the cell's local topology, current internal state, and sensed environment, thus each cell can react to the same hormone differently although all cells have the same decision-making protocol. The method is based on reactive responses such that implemented strategies are a collection of preprogrammed condition-action pairs. Similar to Nagpal's approach, the local rules are defined around specific individual reactions from a communication trigger as oppose to interaction and reaction between local neighbors.

Classical Design Paradigm

The classical approach, such as systematic design and axiomatic design, creates a good design only when the designer can foresee all the future needs and environments, and thus eliminate the unexpected and the unintended from the process [19, 20]. The performance of the system depends on the knowledge, capability, and innovation of the designer since the designer will absolutely determine the system behavior and functionality. The classical process requires the function and task environment to be well-defined before completing a functional break-down with piece-by-piece design [21]. The end-goal is to generate a single solution that will be precisely replicated such that users can expect an exact functionality, even if most engineers admit that many equally good solutions can exist.

The classical engineering process has produced most of the current technological advances including lunar rovers and microprocessors. While these systems definitely have "complexity" challenges, they have only been designed as "complicated" systems. As Braha points out, 'complicated' does not equal 'complex' [21]. Scientific complexity arises from the numerous actions and reactions that happen in the inter-relationships of the components. The traditional approaches attempt to indirectly consider complexity by simplifying the system and stripping the complex nature of the problem.

In addition, by attempting to impose a top-down approach, the innovative patterns and structures that arise from emergence would be suppressed since only human-conceived global structures would be enforced. Using self-organizing rather than explicit design can leave the system free to innovate its own solutions. The problems that complex systems will confront are not entirely predictable so all the possible solutions cannot be determined or optimized in advance. Complex systems must explicitly leave room for unpredictable task environments and unforeseen challenges.

A META-INTERACTION MODELING APPROACH

The presented approach focuses on the interactive behavior between cells. Interaction is the intrinsic mechanism of complexity. The interactions between the individual cells also collectively result in the global behavior. Even with simple actions and simple rules of interactions, unintuitive and complicated global patterns emerge. The designer must focus on designing the context of the local interactions between components rather than only on the individual functions. In contrast to traditional AI, which addresses intelligence in the individual, this work is centered on the belief that intelligent behavior of a multi-agent system is tied to agent interaction and cannot be understood in isolated individual circumstance [13].

This research hinges on the argument that collectively intelligent behavior in a decentralized multi-agent system can occur from only local interactions, based on simple rules, between simple agents. The goal of this approach is to demonstrate a variety of complex interactions that are achieved with basic abilities and manipulated through parametric variables. It is concerned with the emergent collective behavior as oppose to predicting the precise behavior of individual components.

As mentioned previously, distributing work among cells by a central controller has many disadvantages, so this approach designs the behavior of individual cells such that collective intelligence emerges from the cell cooperation. The system has no central brain, yet the cells must synchronize to produce collaborative motion. The challenge in the self-organizing approach is to achieve specific system functionality rather than simply allowing and observing some global behavior to emerge. In many of the past approaches, the system function is defined by the overall final configuration of the cells where the human designer constructs a target configuration given some functional requirement set. Then a transformation algorithm provides the step process to obtain the target configuration.

However, in this approach, only the end system behavior is significant, not the specific target configuration. There are no predetermined structures as long as the collective system can achieve the desired function. In actuality, it is more likely that the system will not maintain a consistent specific structure. In the behavioral approach, the collective behavior will translate into the end system functionality. Utilizing behaviors can hide low-level details of control and allow for higher-level directives, which are often more intuitive for the user.

Meta-Interaction Model Development

The approach is to identify and then parameterize the local interactive behaviors for each individual to create dynamical variables in the system. The meta-interaction model is abstracted on top of the interactive behaviors through the parametric variables. Once the model can be built, it will provide a guide to understand the possible global function based on the current system profiles, and also a heuristic on how to change the profile based on a desired global function.

Interactive behavioral models such as Reynold's Boids are abstracted upon the identified local interactions. The behavioral models can then be parameterized by weighting and aggregating the different behaviors. The parameters are variables that can be manipulated to change the collective behavior in order to achieve different global functions. Furthermore, these parameters provide an opportunity to analyze the relationship between different interactive behaviors in addition to the relationship with the collective behavior. This tunable mapping between the local interactive behaviors and the collective behavior provides the basis for the proposed design approach. Utilizing the tunable variables, the relationships will be investigated leading to the development of the meta-interaction model. The meta-interaction model can be used to provide information on the indication and prediction relationships between the global function and the local interactions.

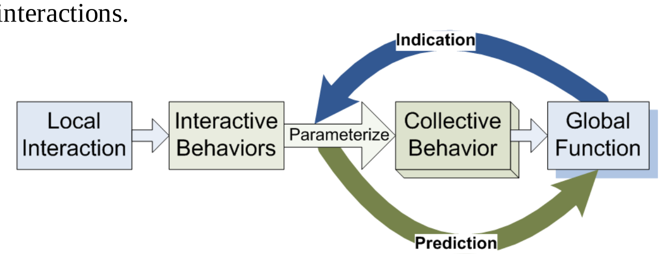


Figure 1: Parameterization of interactive behaviors introduces a tunable mapping between local interactions and global result

The general goal of the meta-interaction model is to provide design information creating a path between the local interactive behaviors and the global function. Essentially, the approach creates a tunable connection between the local and global behaviors. The meta-interaction model is an abstracted layer above behavioral interaction models. The behavioral model is an abstracted layer above the individual cell functions.

Individual Cell Model

The first level of abstraction is to model the individual cells and define their capacity. Admittedly changing cell functions can greatly affect not only the emergent properties, but also change the entire space of possible collective behaviors. With increased functionality of the individual cells, the collective system has more degrees of freedom likely resulting in greater possible global behaviors and functions. However, maintaining simple cells allows the research to highlight the stated focus of interaction. The current purpose is not to study how individual capacity changes collective emergence. In order to focus on the method based on interaction, the individual cell functions will be constrained to a very simple mechanical cell. This also aligns with the premise that useful emergent properties can occur from self-organization from simple cells.

The system will be homogeneous consisting of mobile, circular mechanical cells. Each cell only has 2-D movement such that the decision process is simply to consider in which direction to move. Cells maintain no long-term memory of the environment and have a limited communication and sensing range. As such, cells do not form explicit models or expectations of other agents or the environment. However, in the homogeneous system, all cells are functionally identical, so some implicit modeling does exist.

Specifics regarding how information is obtained through sensors are beyond the scope of this paper. The approach assumes that each cell can communicate wirelessly over a finite spatial locality of communication in addition to perceiving relative positions and velocities of other individuals. Also, the cells can identify like-cells from other environment entities. No cell has knowledge over the global state of the system beyond its local neighborhood. Therefore a cell can be characterized in the simulation by its x-y-coordinate position, its velocity, its physical diameter, and its neighborhood of locality.

Behavioral Interaction Model

The next level of abstraction is modeling the behavioral interactions between cells. This paper uses a behavioral model extended from the Boids model: maintaining a separation distance, cohesion, and alignment. As the cells have no global coordinate system, they can only perceive the relative positions of the other cells. Each cell maintains separation distance by generating a unidirectional repulsive virtual spring from other cells and perceived obstacles. This means that the closer a cell is to an obstacle, the greater the cell wants to move in the opposite direction. The avoidance vector is given by

$$O = \frac{-1}{N}\sum_{i\in\eta}\frac{x_i}{\|x_i\|\|x_i\|} \tag{1}$$

where x_i is the relative position of component i and ($i \in \eta$) denotes iterating over all other elements within the neighborhood. N is the number of other elements that have been perceived, or stated differently, the number of elements inside neighborhood η besides the cell itself. An important consequence to notice is that the interactive repelling force between two neighboring cells is effectively doubled since both cells are repelling from each other. In addition, the vector is undefined when the denominator equals zero; however, this never occurs because two elements will not exist at the exact same location.

Centering, or here-in called cohesion, is implemented by each cell moving towards the average position of all the other cells in its neighborhood. With cohesion, x_i is the relative position of cell i iterated over all other cells within the neighborhood.

$$C = \frac{1}{N}\sum_{i\in\eta} x_i \tag{2}$$

Velocity matching, or alignment, is achieved by each cell moving in the average direction of all the other cells in its neighborhood.

$$A = \frac{1}{N}\sum_{i\in\eta} v_i \tag{3}$$

Alignment is the velocity parallel to cohesion. Alignment is a vector pointing in the average direction of the other cells' movements. Each cell also takes into account its own momentum (M), maintaining some of its previous velocity as inertia rejects change. The simulation estimates velocity by

$$v = x^t - x^{t-1} \tag{4}$$

where t is the current time step and (t-1) was the previous step. Cells also exhibit a small amount of random (R) variation in the selected direction.

The next step is to convert the interactive behaviors into a parametric model. This is done by assigning weights to each type of interactive behaviors, which corresponds to each of the presented vectors. These weights associate with cohesion (W_C), avoidance (W_O), alignment (W_A), randomness (W_R), and momentum (W_M). Each cell takes the above factors into account in generating its decided movement. The change in position, δx, for a single time step is given by

$$\partial x = W_O O + W_C C + W_A A + W_R R + W_m M \tag{5}$$

Substituting each derived term gives the equation

$$\begin{aligned}\partial x = {} & W_O\left(\frac{-1}{N}\sum_{i\in\eta}\frac{x_i}{\|x_i\|\|x_i\|}\right) + W_C\left(\frac{1}{N}\sum_{i\ni\eta} x_i\right) \\ & + W_A\left(\frac{1}{N}\sum_{i\ni\eta} v_i\right) + W_R R + W_m M\end{aligned} \tag{6}$$

Figure 2 is a visual representation of a profile where each weight is equal to one another. In the profile visualization, 'COARM' represents cohesion, avoidance, alignment, randomness, and momentum, respectively.

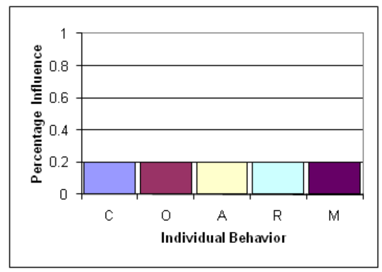


Figure 2: Example Parametric Profile

In the simulated results, the change in position is normalized when the desired step size is greater than the maximum step size resulting in

$$\partial\tilde{x} = \frac{\partial x}{\|\partial x\|}(stepsize) \tag{7}$$

This limits the distance a single cell can take in any given step just like real hardware with speed limits.

Meta-Interaction Model

The last level of abstraction is the meta-interaction model. The goal of the meta-interaction model is to provide a mapping for the prediction of collective functionality from local interactions and for the indication of local interactions based on desired functionality. The collective behavior of the system will emerge from the aggregation of all the reactions and actions occurring through the local interactions, and this collective behavior will translate into the end system functionality. With the parametric approach, profiles can be built based on the relative contributions of the different types of interaction. As the profiles change, the collective behaviors will also change. To form the meta-interaction model, task functions based on collective behaviors must be classified, and then parametric profiles can be categorized into the classification.

The first step is to identify the behavioral trends due to the combination and adjustment of the parameter weights. This will give the general design guidelines on how to tune the parameters in order to achieve specific functions, which are matched to collective behaviors. Within the trends, similar profiles can later be grouped into sets that correspond to certain types of collective behaviors and functions.

With the trend information, designers can control the parameter adjustment in order to manage the system's multi-functionality. To validate the use of the meta-interaction model, it must be shown that multi-functionality not only exists, but can be transitioned through manipulation of the parametric variables that were applied to the interactive behaviors. The categorization of the profiles provides the information guiding the manipulation. The next step will be to simulate the system and use the dynamical variables to analyze the relationships in combinations of interactive behaviors.

SIMULATION ENVIRONMENT

Highly complex systems are difficult to analyze purely through current mathematical theory, thus this work uses computational methods to evaluate the approach. The simulation environment is built on Luke's MASON framework leveraging the Flockers simulation [22]. MASON is a discrete-event multi-agent simulation library built in JAVA. The simulation study is done with 2-dimensional space, but the conclusions can easily be extended to a 3-D space. The environment field is toirodal, which means that exiting the screen on the right will bring cells to the left and vice versa (the same with top and bottom).

The simulation occurs in discrete time meaning that at each time step, agents will be able to go through one decision process: sense the environment, make decision, and perform action. Although real robotic multi-agent systems would likely act in parallel, the simulated agents do not run on parallel threads. However, the approach is not designed around sequential agent actions, and the system does not know which agent will act first. The model maintains no central time so there is no restraint requiring sequential or synchronized actions. This would also be true for parallel processing agents that do not maintain a centralized or synchronized time reference. Furthermore, the agents lack a large memory database, nor do they make expectations for the future. The agents do not explicitly maintain a sense of time, so they do not consider the order/synchronization of actions with others.

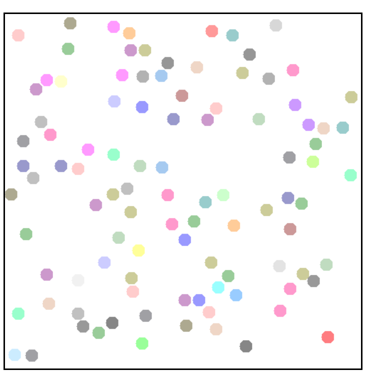


Figure 3: Randomly selected initial positions of 100 cells

SIMULATION RESULTS

It is important to understand the balance between the simple behavioral rules of interaction. To do this, the parameter weights were toggled between various combinations of values. The neighborhood size is arbitrarily set to nine, which is three times the selected cell diameter. For comparison's sake, the same randomly selected initial positions for 100 cells are used to compose the full system in an open toroidal environment as can be seen in figure 3. The cells are initially at rest.

In order to compare different states of the system, the disorder entropy calculation was used as follows,

$$E_d = \ln\left(\left(\frac{1}{2}\right)\left(\frac{1}{N}\right)\sum_i^N\sum_j^N \left\|x_i - x_j\right\|\right) \quad \textit{where } i \neq j \tag{8}$$

The calculation is the sum of the minimum toirodal distance between each cell coupling ***i-j*** divided by the number of cells N in the system. The equation equates decreased disorder with a more tightly packed system.

Under pure cohesion, the cells cluster into many small groups exhibited by figure 4. The cells do not cluster into a single group because they do not have an infinite view of the world. Individual cells and small groups may not be aware of the existence of the other small groups. The cohesive equilibrium arises from the simulated physical constraints that do not allow the cells to move closer from cohesion.

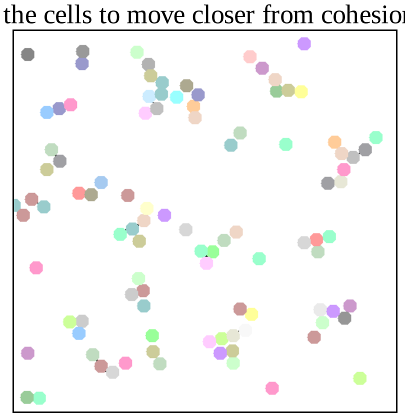


Figure 4: Pure cohesion after 30 time steps

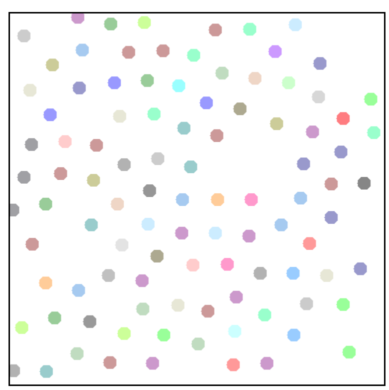


Figure 5: Pure avoidance after 30 time steps

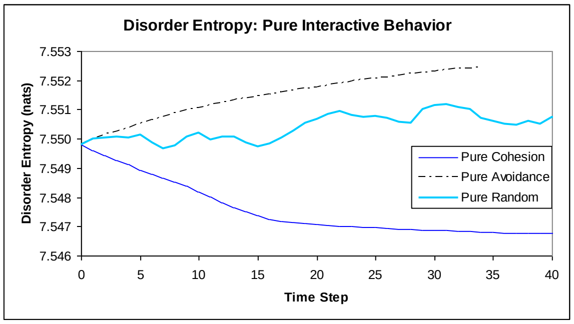


Figure 6: Disorder entropy of pure interactive behaviors

Under pure avoidance, cohesion's counter-part, the cells distribute themselves in the available space in order to maximize distance between all the cells as exhibited in figure 5. If a new cell was suddenly inserted into this separated system, it would force many cells to redistribute and accommodate the new density because of the many reactions that would propagate through the system.

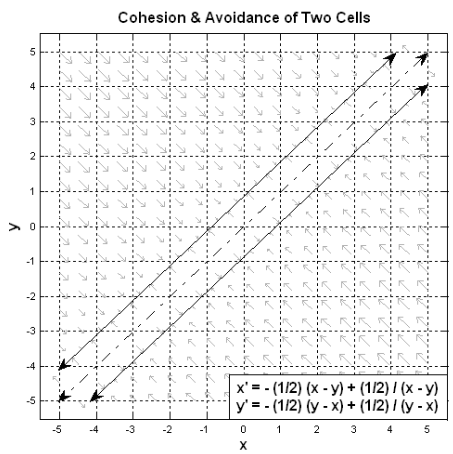


Figure 7: Cohesion-avoidance combination phase plane plot of 2 cells. x and y represent the absolute location of the 2 cells.

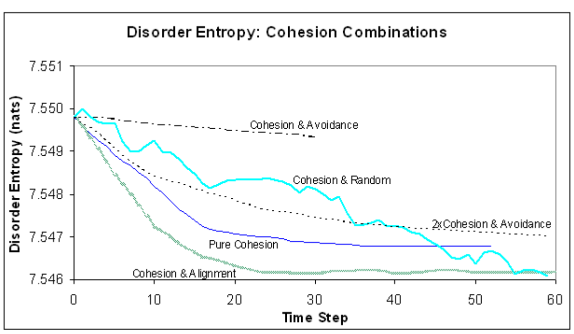


Figure 8: Disorder entropy of cohesion combinations

Alignment and momentum do not have any effect without some type of initial velocities since they are calculated based on velocities. This means that a system that starts at rest will not change based purely on alignment or momentum.

In figure 6 the pure interactive behaviors are related through the disorder calculation. Cohesion tends to decrease the disorder while avoidance results in the opposite. Pure uniform randomness presents no discernable trend.

The combination of cohesion and avoidance acts to create a 2-cell solvable target separation distance. Figure 7 shows the phase portrait for two cells in 1-dimension using cohesion and avoidance. The absolute locations of the two cells are represented by 'x' and 'y' and the equilibrium points are shown with the solid double arrow lines. This corresponds to the separation distance. Besides the points where the positions of the two cells are equal and cannot be solved represented by the dotted line, all points lead to the equilibrium lines. It is important to realize that these plots are only true when the cells are within each other's neighborhood.

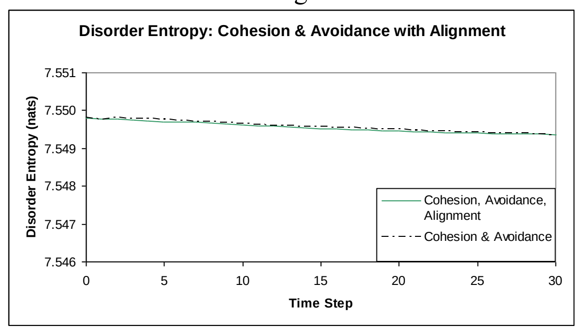


Figure 9:Disorder entropy of cohesion avoidance and alignment

In figure 8, pure cohesion definitely has a relatively greater decline in disorder while the cohesion-alignment combination reaches an even lower value. In addition, doubling the cohesion weight in the cohesion-avoidance combination allows the cohesion contribution to make a greater impact and decrease the disorder of the system reinforcing the previously discussed separation distance. The cohesion-randomness combination does have an overall drop in disorder, but the random effect is definitely visible. The interesting result here is that the alignment contribution in addition to cohesion reaches a lower disorder. With alignment, cells continued to move because of the collective velocity of their neighborhoods. Basically, when groups of cells would normally stop after reaching a point of cohesive equilibrium based on pure cohesion, the cell and cell groups continued to move based on the collective momentum of the neighborhood.

However, when alignment is added to the cohesion-avoidance combination, the end result between the two combinations of parameters do not produce significantly dissimilar results as emphasized by figure 9. At first, this may seem confusing, but it can be better clarified by considering the case where there is an increased amount of alignment. To further emphasize, adding momentum to the cohesion-avoidance-alignment combination also has a significant effect.

While at first alignment had no significant visible effect, this is due to the fact that the collective momentums of the groupings were so low that the contribution from alignment was dominated by the cohesion and avoidance contributions. After alignment is increased, a significant change in the collective behavior of the system becomes visible. Additionally, if instead of increasing alignment, momentum is added, a similar significant change in the collective behavior of the system occurs. By increasing each cell's momentum, the collective velocity of each neighborhood is also increased. By increasing alignment, the impact of the collective velocity of each neighborhood is increased. The end result is that the alignment term can overcome the domination of the cohesion and avoidance contribution.

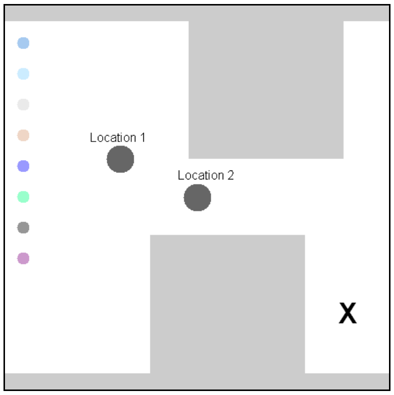


Figure 10: Search environment

The system still forms clear gatherings of cells; however, the gatherings have a continual flow of movement. Continuous fluidity is achieved by introducing momentum into the system such that the cells will maintain some speed. Furthermore, alignment is needed for collective motion in synchronized shared directions. Because of the continual movement, the groups are no longer separated in several smaller groups. As the cells move, the different groups intersect and merge together to form a larger single group. This continual flow of a cohesive group is the emergence of the collective behavior called flocking.

Searching

One of the difficulties in only giving each cell a small locality of sensing is that there may be no cell that is aware of target objects or locations. Figure 10 shows two locations that contrast varying difficulty of discoverability. In order to simplify the analysis, the number of cells considered in the system was eight. The grayed areas represent environmental obstacles.

Generally, the cells can discover target location 1 more easily than target location 2 because of the obstacles covering location 2. An increased average avoidance weight in the system would produce a swarm with a wider search net, which can make discovering some open locations quicker. In this case, avoidance causes the cells to veer away from the obstacles making location 2 difficult to find. However, without obstacle avoidance, cells would run into each other and the obstacles.

Of course, analyzing the system behavior is not as simple as tuning a single weight. Avoidance works in conjunction with cohesion to define the separation distance between cells. Increasing cohesion yields similar results to low avoidance where the swarm tightly gathers and has a smaller sensor net field. Intuitively, to increase the search field, a lower cohesion weight should be used. However with low cohesion, if one cell were to discover the passive object, the other cells would not be as inclined to follow.

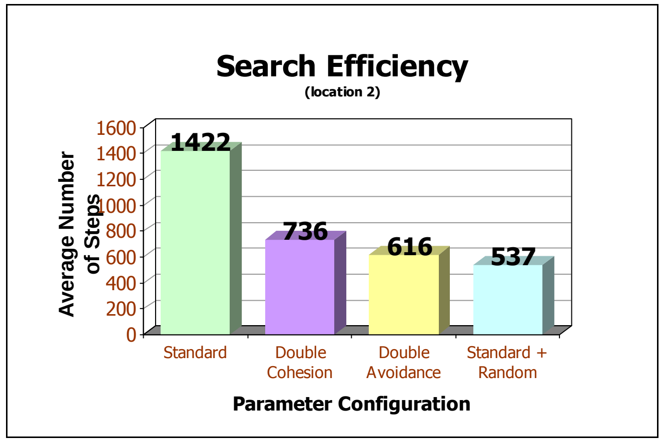


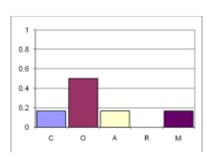
Figure 11: Search comparison with the standard profile chosen as equal contributions from cohesion, avoidance, alignment, and momentum while having no randomness.

Figure 11 compares the average amount of time steps the system needed in order to discover the passive object at location 2. This shows that the increased disorder from avoidance does yield a quicker search than the standard combination, although not much quicker than from increased cohesion. Adding randomness has the best overall effect which indicates that increased uncertainty helps deal with the uncertainty in search applications. While disorder does seem to have some relation to search ability, because of the coupled nature of disorder with obstacle avoidance, depending on the environment, the relationship between disorder and search efficiency is not directly proportional.

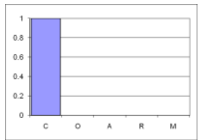
Preliminary Insights into the Interactive Behaviors

The behavioral examination was initiated in order to gain insights into the relationship of interactive behaviors. The following key points and representative profiles summarize the different findings. Further work will fully categorize the ranges of profiles that match identified behavioral trends.

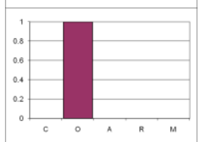
1. Managing obstacles requires avoidance



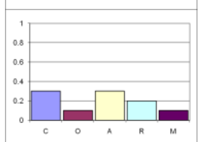
2. Aggregation, Joining, Attaching, Compacting, centering



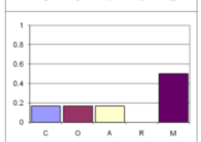
3. Scattering, Dispersion



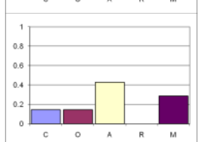
4. Specific group demand requires decreased disorder



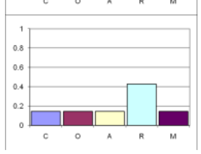
5. Momentum gives continuous fluidity



6. Alignment gives synchronized fluidity



7. Increasing uncertainty in the system deals with application search uncertainty



Using these insights, the designer can identify interaction behaviors for different functions. Essentially, by controlling the parametric variables, the system's mechanical implications can be manipulated. In most cases, different ratios and combinations of interactive behaviors will be required. It will rarely be as simple as using a single behavior. The hard task is simultaneously handling both uncertainty and a specific demand.

Example Application

The following are typical simple mechanical tasks: formation, synchronized group motion, exploration or searching, coverage, containment, surrounding, pursuit, evasion, and following. Most applications will require a combination of tasks either simultaneously or sequentially. As an example task application, consider the case of search-and-surround. Search-and-surround applications include hazardous waste cleanup, bomb detection and removal, and disaster survival rescues. A natural system parallel would be the human immune system where white blood cells continuously swarm through the body searching for foreign substances to eliminate.

The complex system provides many advantages to the search-and-surround problem. First of all, as the number of agents multiplies, it will become impossible for a central commander to coordinate the search task for the numerous agents. This approach is fully distributed not relying on any central control or global information. In addition, the search-and-surround applications often occur in hostile and unpredictable environments whether in enemy territories, unexplored regions of the space and the ocean, or natural disasters like earthquakes and storms. The agent swarms must be able to adapt to the situation without the need for *a prior* knowledge of the specific hazards that might be encountered.

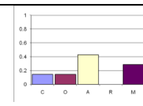
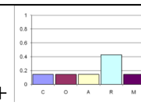
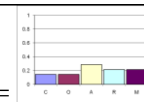
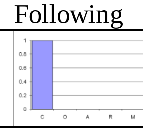
Phase 1: Exploring / Searching	
Behavior:	Synchronized Continuous Motion + Uncertain Directions
Parameter Profile:	 +  = 
Phase 2: Surrounding	
Behavior:	Following
Parameter Profile:	

Figure 12: Representative profile for phases of search-and-surround

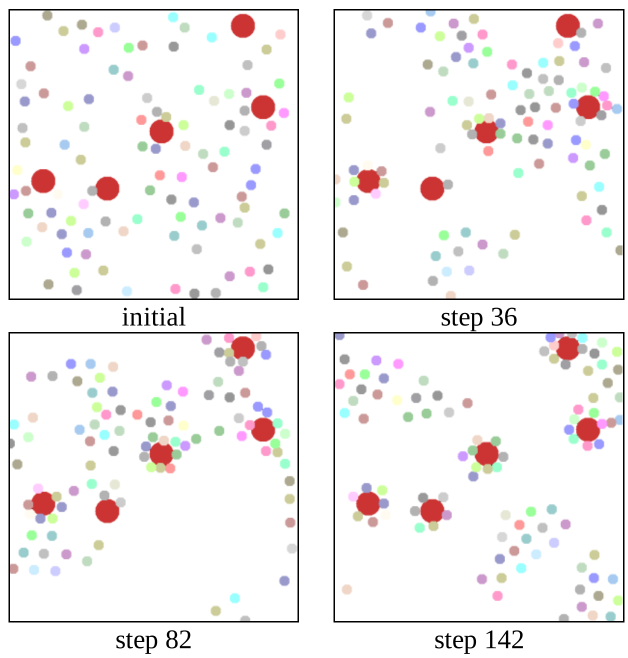


Figure 13: Search-and-Surround example. There are 100 cells searching to surround the 5 big red objects.

This task requires two phases, the first of searching and the second of following. Many cells following a stationary object has the consequence of surrounding so the second phase will require cohesive groups. The first phase can preemptively form groups for the second phase by utilizing synchronized directional motion in the search as oppose to random individual searches. Thus, search-and-surround should tune with a reliance on randomness, momentum and alignment, and then transfer to a dominance of cohesion after the object is found. Just to note, some avoidance is required so that individuals do not run into each other. Figure 12 shows each phases required behavior and parameter profile matching.

Figure 13 exhibits an example simulation of 100 cells searching to surround 5 big red objects in an open environment. From the initial positioning, two of the objects are quickly discovered and surrounded. Consequently, the cohesive behavior of the cells draws more entities to that general location. However, since the objects have already been surrounded, the new cells cannot latch onto the central position of the target objects and thus continue moving in search of other objects. By step 142, the five objects have been surrounded and the remaining cells continue to search for other targets.

The cells can more quickly discover objects in the open space with higher disorder entropy from random movements and increased separation. Furthermore, because the cells are constantly interacting implicitly through the collective behaviors, objects can be quickly surrounded rather than waiting for each individual cell to discover the object on its own. When cells move as a group rather than individually, an object is quickly encompassed after discovery. The method is fully distributed without any explicit cooperation between the simple cells. This search-and-surround simulation is a simple demonstration of one application.

However, it must be pointed out that for simulation purposes, the change between phases was hard-coded into the cells as a response to discovering the target. This is the same as hard-coded DNA in white blood cells that automatically attack foreign substances. The meta-interaction model currently only provides information on the profiles required to achieve the functions in each phase and does not yet identify learning or communication methods that trigger the phase changes. The triggering mechanism may be based on other mechanisms such as Nagpal's gradients or Shen's DHM [15-18].

FURTHER VALIDATION REQUIREMENTS

The meta-interaction model based on parametric behavioral weights has been introduced and applied to a representative multi-robotic application. The approach can easily and quickly be applied towards systems with behavioral models. It provides a method to manage multi-functional adaptive ability by exploiting dynamical variables that can be easily manipulated to change the overall behavior of the system. This approach lends itself well to further developments in using control feedback design, learning methods, or evolutionary algorithms, especially those that require heuristic guidance. However, there are a few key aspects that still require verification.

Firstly, with any non-linear complex system, stability must be analyzed. One of the major challenges in these types of systems are the nonlinear effects such that little changes in initial conditions will consequence in drastically different outcomes. Consequently, users and designers can never deterministically predict the system behavior. However, with this approach, there is a major difference with many traditional complex systems because the end functionality is based on the collective behavior as oppose to specific formations. Because of this, it is difficult to use traditional stability approaches based on coordinate positions to identify basins of attraction, stable cycles, or sink nodes. The current mathematical techniques provide limited capability towards solving this complex system, so a computational, statistical approach will be relied upon. The next step is to complete a statistical study by characterizing the resultant global behavior from many different initial conditions to ensure a statistical confidence of expected behaviors from the same parameter profiles. This will then needed to be expanded to show that emergent functions will not violate possible safety and performance requirements.

This will require the system's collective behavior to be characterized in order to properly compare different trials. Much of the current research has relied on qualitative observations from engineers to define whether the collective behavior provides functional emergence. For collective animal behavior, different metrics that have been suggested are various density functions such as coupling distance; polarity, which describes the directional alignment of individuals [23]; and nearest neighbor distance. The statistical approach will demonstrate if these metrics are sufficient or if further measures must be identified.

Finally, the meta-interaction model should further demonstrate multi-functionality through additional mechanical task applications and implications. It should also be shown that the general trends represented by the meta-interaction model hold even in slight variations of behavioral implementations in different multi-agent systems. However, it is not expected that the described meta-interaction model would work for dissimilar systems with different simple behaviors as the model is abstracted upon a specific behavioral model. But after validation, the meta-interaction model approach should be feasible for other multi-agent systems with different behavioral models.

CONCLUSIONS

This paper has presented a meta-interaction model based on behaviors in order to help design self-organizing, complex systems. The relationships between the simple behaviors of cohesion, avoidance, alignment, momentum, and randomness were investigated. The concept is to understand the space of possible collective behaviors by focusing on simplified classes of group behaviors. From there the paper showed how the interactive factors affected the collective behaviors. The exhibited implications from the interactive behaviors are as follow: managing obstacles requires avoidance; aggregation and dispersion are controlled through cohesion and avoidance; group demands requires decreased position disorder; momentum provides continuous fluidity; alignment gives synchronized fluidity; and uncertainty in the system can deal with application search uncertainty.

Through this process, an approach based on the behavioral interactions within the complex system is introduced that once fully developed can principally be applied towards the design of complex, adaptive systems. Further behavioral trends will be studied such as the onset of synchronized directional motion from varying amounts of alignment.

While the approach still needs certain validation studies such as stability, once validated, it can easily lend itself towards control feedback, evolutionary methods, and learning approaches. Future research can combine these techniques such that the system can self-discover new system behaviors, and thus functionality. Currently, the system objective is defined extrinsically by a human programmer, but it can be adjusted to be intrinsic based on fitness functions or even simply survival.

Of course, the classical engineering approach may still be ideal when the environment can be well-defined along with the required functional specification. Self-organizing based complex systems excel in complex environments containing unforeseeable circumstances because engineers cannot predict all the possible contingencies that may be encountered. Complex systems can provide the adaptive ability in order to manage such uncertainties that classical systems cannot. On the other hand, complex systems gain adaptive ability at the compromise of predictable determinism. Pure self-organizing systems may not be the optimal solution towards many tasks, and a hybrid system combining deterministic hierarchical approaches with complex self-organizing methods may prove promising for further research.

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