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DESIGN OF CELLULAR SELF-ORGANIZING SYSTEMS

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ABSTRACT

Technology development is facing increased challenges as engineers begin to tackle the problem domains with greater uncertainty. Future engineered systems must be able to function in unpredictable environments such as deep ocean, rough terrain, and outer space while performing uncertain tasks like hazardous waste cleanup and search-and-rescue missions. Furthermore, the increasing size of engineered systems introduces unplanned interdependencies of components. Complex systems can provide the adaptability in order to manage uncertainties that traditional systems cannot. As the uncertainty of the problem domain increases, engineering design methods must be advanced in order to properly address the changing needs and constraints. This paper proposes a new approach inspired by natural phenomena in order to extend the design envelope towards an *artificial nature*. This approach broadens the traditional design and re-design methods by utilizing the self-organization process exhibited in natural systems. From a design point of view, the critical question is: *how can system adaptability be designed into complex systems based only on local interactions between (many) simple cells?* The goal is to design systems that excel in hostile and unpredictable environments where it is impossible for the designer to conceptualize every possible contingency. The key is to focus on the interactions and behaviors of the system. In this paper, we suggest a *meta-behavior model* for cellular self-organization systems that can be used as a design approach to guide emergent function capacities.

INTRODUCTION

Designing complex systems has become a major challenge and research topic. 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 and reliability of many interacting agents. An agent is an entity or computational process that senses the environment and acts on it. Flexible multi-agent systems actively alter their overall structure and inter-relationships, translating into great versatility. An approach to implementing these systems 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 cellular biology, fish schooling, and locust swarms.

Complexity raises from the multitude of interactions and reactions that exist in a many entity system. Self-organization is the idea that the many individuals will organize into societies based only on local rules and local communication. It is large scale organization through limited local interactions of the

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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 [1-6]. Self-organizing systems can accomplish tasks with simple individual behavior and components, requiring simple programming and simple component architecture. This not only decreases the manufacturing expense but eases hardware development and maintenance. Furthermore, self-organizing systems rely on local processes and distributed control, leading to high level theoretical scalability.

However, the traditional engineering design process has not been well-adjusted to design these complex, self-organizing systems. While designers realize we must take a different approach towards complexity, so far, design has only addressed complicated systems. In order to take the design methodology one stop closer towards truly designing complex systems, we propose a cellular self-organizing (CSO) approach to developing complex adaptive systems. In the CSO framework, we consider a system 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. The objective is to extend the envelope of design processes into the realm of non-deterministic design problems and solutions.

What are the advantages of CSO systems that make them compelling solutions? The critical advantage of CSO multi-agent systems is the adaptability, 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 the 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 behavioral rules of separation and movement. At a deeper micro-level, cells combine to form complex structures based on DNA information. In addition, in the human immune system, white blood cells continuously patrol and protect in a very distributed way. By relying on vast numbers of resource-limited and unreliable cells, cellular systems achieve reliability even in cell death, varying scale, and uncompromising environments.

Utilizing complex systems in the creation of artificial systems is inspired by the perseverance of natural systems. In the many complex self-organizing natural systems as discussed, many emergent advantages are exhibited. While it is impossible to make a perfect system such that the system is better than every other system in every way, there are many general advantages associated to the adaptability of CSO systems.

1. Versatility & Multi-functionality – The key advantage is the ability to restructure, thus a variety of forms can be realized. This allows the system to dynamically respond to multiple and changing tasks. Some tasks require many different functions, especially when these functions may not all be initially foreseen.

2. Reliability –The large number of similar agents provides redundancy such that the failure of a single cell does not destroy the effectiveness of the system. In addition, with distributed control, there is no single central command unit failure that will cause critical catastrophe for the system. Another means by which complex systems maintain robustness has been termed degeneracy, which is multiple processes with identical consequences [7]. Basically, the ability to do the same thing with multiple processes for achieving the same function makes it less likely that a single type of disruption can prevent functionality.

3. Evolvability - The ability to grow and develop completely new functionality. Once the system is given the empowerment to create new forms and functionality, it will become truly adaptable to unperceived circumstances as the system will actually grow and increase its functional space after deployment.

Furthermore, CSO systems are generally scalable and can be inexpensive to manufacture. They are ideally scalability as a consequence that most processes are performed locally. Because these systems are designed around the concept of massive population and distribution, they are theoretically scalable from medium teams to very large teams; however, realistically, there will be a lower and upper limitation to the resolution (population size) of the system.

Due to the possibly simple architecture of each individual cell, the cost of manufacturing is kept to a minimum. In addition, since each cell does not require abundant processing, so complex software is not required. Agents only rely on a local neighborhood of communication, so high power and high bandwidth communication hardware does not need to be integrated

In the rest of the paper, we first review the related work. After that we discuss the new way of thinking for complex systems design. We then outline the CSO design process using behavior based models. Finally a simple example is presented. Future work and concluding remarks are described in the last section.

RELATED WORK

Bringing the natural processes of self-organization and emergence to multi-agent system is not a new idea. Self-organization has been used to study many natural systems such as chemical pattern formation, traffic jams, termites, and ant social behavior [8-11]. Much engineering research has focused on copying structures and behaviors of natural systems. Many

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of the observed natural techniques and principles 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. 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.

Many research groups have developed different techniques for multi-agent systems to achieve natural-like processes. 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]. However, this method constrain the system to preconceived structures dependent upon human understanding and creativity. In another approach, Nagpal focuses on the construction process itself developing a language for instructing a sheet of identically-programmed agents to assemble themselves into a predetermined global shape [16]. The process is sequenced, triggered, and communicated through the cells of the sheet by means of a gradient message.

Another distributed communication method for task execution is the bio-inspired Digital Hormone Model, DHM [17]. With DHM, each component of a swarm can communicate via hormones and execute local actions via receptors. The method is based on reactive responses such that implemented strategies are a collection of preprogrammed condition-action pairs. Similar to Nagpal's approach, local rules are defined around specific individual reactions from a communication trigger as oppose to interaction and reaction between local neighbors.

While all of these techniques and systems have been important to advancing multi-agent swarm systems, they have all centered around specific system developments without specifically addressing the general engineering design challenge. This paper aims to progress our design understanding of cellular, self-organizing systems.

Methodologies in Design Theory, such as Axiomatic Design [18] and General Design Theory [19], have a different focus than traditional science theory, which analytically observes nature in order to discover and describe the natural behaviors [20]. Design Theory centers on processes humans can use to produce functional systems. Figure 1 shows the Systematic Design [21] process, which was developed through years of observing the natural engineering design practice where design is approached from a systematic and practical point of view. It looks not only at the defined problem but also at the surrounding environment. The design process can be divided into four main steps: the planning and clarifying the task phase, the conceptual design phase, the embodiment design phase, and the detail design phase. This is all followed by the replication and distribution of a single solution.

The classical approaches in Design Theory creates a good design when the designer can predict and identify all the future needs and environments, thus eliminating the unexpected from the process. The performance of the system predominantly depends on the knowledge and innovation of the designer since the designer will absolutely determine the system form and functionality. The classical design process begins with an exact specification of the requirements of the system. This requires the task environment and the function to be well-defined. The needs are formulated as thoroughly as possible on the assumption that the final intended design will never work outside these needs and constraints.

After this design specification, the next step is often to perform a hierarchical functional break-down which will be followed by piece-by-piece design [22]. Of course, there may be some zig-zag in the design specification and functional solution as the conceptual design becomes more complete and detailed [18]. However, regardless of the early zig-zag evolution, the end-goal is to generate a single solution that will

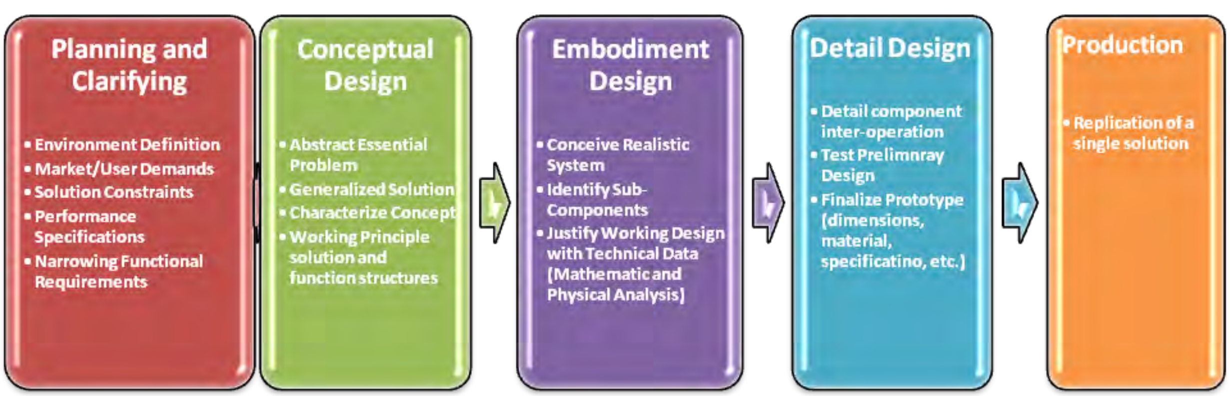

Figure 1: Example Parametric Profile

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be precisely replicated such that users can expect an exact form and functionality, even if most engineers admit that many equally good solutions can exist.

This classical engineering process has produced most of the current technological advances that have been realized including space shuttles and microprocessors. While these systems definitely have “complexity” challenges, they have only been designed as “complicated” systems. As Braha [22] and Sumpter [23] point out, ‘complicated’ does not equal ‘complex.’ Scientific complexity arises from the numerous actions and reactions that happen in the inter-relationships of the components. This complexity gives rise to a whole system that is much more than simply the additive sum of the component parts. The traditional approaches attempt to indirectly consider complexity by simplifying the system and stripping the complex nature of the problem. By stripping the inherent complexity of the system, the system loses the advantages gained through the complexity. Moreover, 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.

Specialized robots will likely always be better at their specific actions, but for tasks that require a variety of actions, the specialized robots will not be able to complete the mission. For a given set of tasks, robot designers can consider the known factors during the design phase in order to satisfy the task requirements; however, it is difficult and sometimes impossible to design a single robot that can meet every task requirement for some applications. Moreover, in many missions, the designer often cannot foresee all environments and requirements that are possible and necessary. Research in the design field have recognized the need to develop design methodologies to address design of complex systems [22, 24], but few approaches have been fully outlined.

DIFFICULTY IN DESIGNING CSO SYSTEMS

While natural systems have had the luxury of evolution over millions of years, in the engineering world, achieving bottom-up adaptability by design represents a major challenge. With emergence, the designer does not know what will happen. One method is to use purely empirical approaches, which implement human conceived understandings of natural systems into a simulation and then observe the emergent responses. However, this strongly relies on trial-and-error and can be difficult as an engineering tool.

Applying traditional processes in the design of complex systems runs into difficulties in the first step of planning and clarifying the task. Clarification of the task requires defining the functional requirements and the problem environment. While this process has created systems with complexity, the process was not completed under the nature of complexity. Instead, only complicated systems were created and complexity is not the same as complicated.

As an example, space shuttles are both a complicated and complex system, but the design process in creating the space shuttle only looked at the system as a complicated system. A space shuttle that has the requirements of making a round-trip voyage from earth to mars is very difficult; however, we exactly specify the functional need and the environment of operation. The challenge holding designers back is not the complexity of the system or the environment but the lack of resources like technology. In essence, we know how to do it, but the technology is not yet there.

Complexity is based on the difficulty to understand the relationship and reaction in all the interactions of a many component system. As system size grows, many inter-dependencies in the components unknowingly develop. The uncertainty in a design problem sources from the designer's inability to understand all of the relationships in the environment, target functionality, and system form. Using self-organizing and emergence rather than explicit design can leave the system free to innovate its own solutions. The problems that CSO systems will confront are not entirely predictable so all the possible solutions cannot be determined or optimized in advance. CSO systems must explicitly leave room for unpredictable task environments and unforeseen challenges.

Traditional design relies on a complete knowledge of the problem statement, but complex systems are advantageous in applications where this knowledge is incomplete. Especially because the problem domain cannot be completely specified, the functional domain is also uncertain. Traditional design methodologies rely on deterministic information, therefore there is a gap in the design process between the problem domain and finding a solution in the solution domain.

GAP IN DESIGN KNOWLEDGE

If a problem could be one-hundred percent perfectly specified and the solution can be achieved from completely understood technologies, then a computational automatic process can be applied to define the solution. Engineers are constantly pushing this knowledge envelope as more and more processes become automatic. Designers step in once there is at least a small amount of uncertainty and knowledge such that a choice must be intuitively selected from several possible solutions based on a top-down functional objective.

Nature works in the completely opposite way. There are vast amounts of simple building blocks that react to local environments and interactions to form emergent structures. Besides survival, there is no specific function or structure enforced by a functional break-down and hierarchy. As humans study and observe nature, the exact behaviors, motivations, and processes of the different natural systems are difficult to identify and replicate. Even after mimicking some systems, there's question in how perfect the knowledge is about the system. So far, we can only observe and copy natural systems.

Design of CSO systems will end up falling somewhere in between the two extremes of human computational automation

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and natural behaviors. With modular-reconfigurable robotics, computer scientists attempt to optimize specific system configurations. Ecologists and evolutionary biologists study natural systems with the objective to understand the exact behaviors and processes. Design of CSO systems will use nature-inspired approaches to develop artificial systems but must overcome the solvability challenge of the inherent massive dependencies. The CSO approaches will address these issues and extend the envelope of design methodologies deeper towards natural methods.

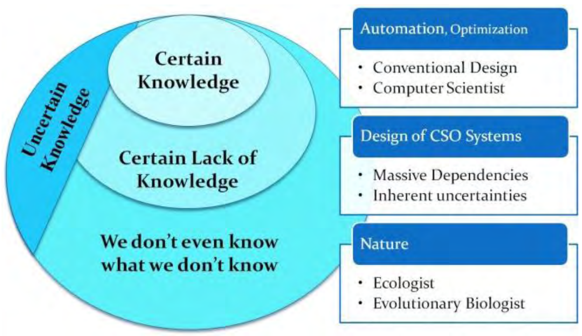

Figure 2: Design Knowledge Envelopes

In the early phases of design, designers already realize that they lack some knowledge or there is uncertainty in their knowledge, whether it be in the task environment, customer requirements, functional specification, available technologies, etc. In general, there are 4 main zones exhibited in figure 2.

1. *Certain You Know:* This is the information that you are absolutely certain you do know. This is the space that Designers tend to work in, exactly specifying details such as functional requirements, environmental constraints, and solution form.

2. *Certain You Don't Know:* This is information that you are absolutely certain you do not know about. Designers often put this case as a fifty-fifty chance and tend to avoid this space.

3. *Uncertain You Don't Know:* This is the realm of nature and the abyss of the unknown. Current scientific knowledge does not know the vastness of the world and the information out there. Engineers and scientists cannot be certain how much they do not know. Natural systems fall into this space. Human knowledge is repeatedly discovering new details about nature that was previously unknown. A prime example is the quantum mechanics breakthrough after Newtonian mechanics.

4. *Uncertain You Know:* This space is really the space of things the designer knows but may have not even realized. The argument is that this space is related to intuition, creativity, and experience. Intuition is basically not knowing what we do know. Creatively new and practical solutions are unproven ideas we knew but had not previously realized. It may work more on sudden instinct rather than rigorous processing.

Regardless of how much the designer admits to know or not know, in the end, with the traditional design process, the designer must make executive decisions specifying an assumption of certain knowledge. Stated another way, as designers solidify the final design solution, they must make final decisions on the assumption that they are certain about what they know. They will exactly specify the task environment, the functional requirements, the solution form, and the functional behavior. If the system fails outside the specified bounds, it is not the designs fault.

The Demand-Supply Relationship of Complexity

In the design process, the *demand* is the design problem and the *supply* is the design solution. As Ashby points out with the Law of Requisite Variety, "variety absorbs variety, defines the minimum number of states necessary for a controller to control a system of a given number of states" [25]. CSO approaches will develop complex solutions that offer increased functional capacity, although at possibly decreased efficiency, and thus should be used for matching problem demands.

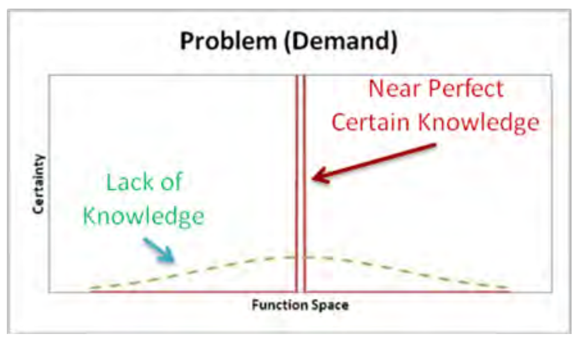

Figure 3: Problem Demand Curve

The above figure displays two example problem demands curves. The solid curve represents a demand that is peaked at one point in the problem space. There is absolute certainty about the needs of the problem and it is at one known point. The designer knows exactly the necessary function, and the problem can be specified with absolute certainty. This matches the sharp top-down breakdown in conventional design. On the other hand, the dotted line more closely exhibits natural problems. We have a guess at what the problem is but we really do not know everything about it. The design demand represented by the dotted line curve shows an uncertainty of the required function.

A similar and parallel figure can represent the supply side. With traditional design, designers take the specific problem and endeavor to create a product that performs a single solution at a very high certainty. The dotted line represents a system that might have many forms and perform many functions. There is

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wider functional capacity range with many run-time possibilities, but less certainty in the specific function. Note that the y-axis does not represent efficiency of the solution, although there may be some correlation with efficacy and the certainty in the design solution, which can be explored in future research.

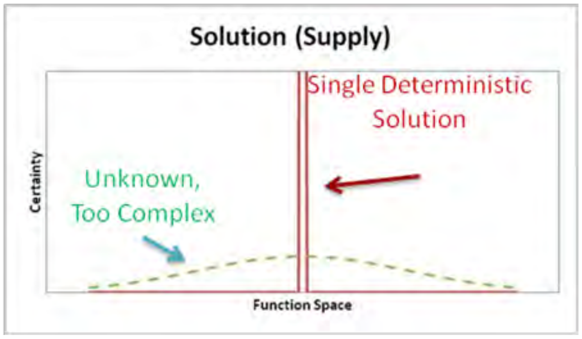

Figure 4: Solution Supply Curve

Ideally, designers could create systems with both a wide and tall supply curve where the solution could achieve many solution instances with a high certainty. However, design research can only take small steps in reaching this ideal. The CSO processes takes this step with objective solution curves lying in between the two extremes represented in figure 5. Essentially, CSO prepares an emergent capacity as oppose to designing one specific function capacity. This does trades some determinism for a variety of functionality. CSO solutions have an increased function space in order to fulfill demands with uncertain space. Originally, we have no idea what might emerge, but with the CSO approach, we will guide emergence so we can at least know a little.

Figure 5: CSO Demand Supply Medium

DESIGNING CELLULAR SELF-ORGANIZING SYSTEMS

Complex systems are expected to excel for problems where the task environment or the functional requirements are not completely known. The CSO approach recognizes that to design for uncertainty in the problem, there must be uncertainty in the solution. CSO explicitly designs for unpredictable task environments and unforeseen challenges. The specific uncertainty in the solution consequences in the adaptability carried by CSO systems. This adaptability is a direct trade-off with determinism. The designer must initially accept that not all possible solutions will be humanly determined and even appreciate the inherent knowledge limitations. The system will be engineered with partial ignorance [22].

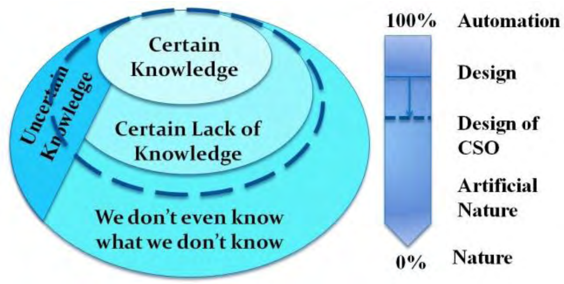

Figure 6: Extending the Envelope of Design Processes

Exhibited in the above figure, the CSO approach will push the envelope of design techniques further into the spectrum and closer towards natural processes. There is a realization that the designer does not know what the possible solution forms might be and plans to take advantage of the natural process of self-organization in order to allow solutions to emerge.

Behavioral Based Design

Behaviors are how a cell acts given the observed environment and current cell state. The CSO approach uses Behavioral Based Design (BBD) rather than focusing on form. The challenge in the CSO approach is to achieve specific system functionality rather than simply allowing and observing some global behavior to emerge. Many other solutions for multi-agent robotic systems focus on creating specific forms, and those forms translate to functionality. 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 collective 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 BBD, the collective behavior will translate into the end system functionality.

In BBD, the functionality results from the collective system behavior. In fact, the global system form is likely to be amorphous in a sense that it may be constantly changing. This amorphous form will emerge from the self-organizing behaviors of the constituent components.

Restricting system solutions to specific forms is not conducive of the self-organizing design approach. In addition, it enforces human conceived forms thus constraining the system functionality to human conceived solutions, which contradicts

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the spirit of CSO design. The particular forms are specialized solutions for a single function, and in the end, nature will punish the specialist that cannot adapt. Furthermore, by focusing on the behaviors of the system, the designer can hide low-level control details and concentrate on the high-end design problem.

Specifically, designers can focus on the interactive behavior between cells. Keying in on interaction brings the designer closer to the source of complexity, and thus the source of adaptability. This approach does not look for a single solution form but centers on the component interactions. The pooled interactions between the individual cells collectively result in the global behavior. Even with simple actions and simple rules of interactions, unintuitive and complicated global patterns emerge.

In our Behavioral Model (BM), we breakdown and isolate simple component behaviors. Example component behaviors are attraction and repulsion. These component behaviors can then be paramerized and linearly added. This sum results in the end action of the cell. These relationships are shown in the following equations.

$$BM = \{B\} = \{B_1, B_2, ..., B_m\}$$

$$f(BM) = W_1 B_1 + W_2 B_2 + \cdots + W_m B_m \Rightarrow action(a_i)$$

The parameter coefficient weights, W_i, lay the basis for the Meta-Interaction Model (MIM).

The Meta-Interaction Model

This CSO approach utilizes the Meta-Interaction Model (MIM) [26], which focuses on the intrinsic property of complexity: interaction. The MIM is abstracted on top of the BM through the variable parameters. The implication of using the MIM approach is the introduction of a new design space based on the parameterized behaviors. This design space consists of tunable variables that controls the behavior of the system and it connects behavior to emergent function capacity.

MIM 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. It is concerned with guiding the emergent function capacity as oppose to precisely determining a single function capability. The designer must focus on designing the context of the local interactions between components rather than only on the individual functions. This combines top-down design with bottom-up self-organization.

A MIM has been developed for the extended-Boids model [12], COARM, which uses the simple behaviors of cohesion, avoidance, alignment, momentum, and randomness [26]. In the equation below, the COARM behavior set is multiplied by the parameter matrix and linearly combined. This results in the oriented function capacity.

$$\begin{bmatrix} FC_1 \\ FC_2 \\ \vdots \\ FC_n \end{bmatrix} \Leftarrow \begin{bmatrix} W_C 1 & W_O 1 & W_A 1 & W_R 1 & W_M 1 \\ W_C 2 & W_O 2 & W_A 2 & W_R 2 & W_M 2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ W_C n & W_O n & W_A n & W_R n & W_M n \end{bmatrix} \begin{bmatrix} C \\ O \\ A \\ R \\ M \end{bmatrix}$$

Each row represents one parameter profile leading to one function capacity. The following figure exhibits an example visualization of a COARM profile with uniform parameter weights.

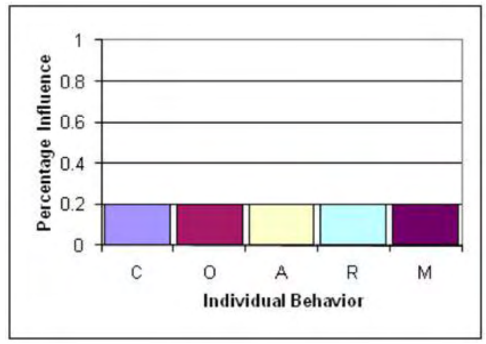

Figure 7: COARM Paramter Visualization

The trends and relationships in the parameter matrix are more important than specifying absolute numbers because at this point, we can only guide expected capacities as oppose to defining specific capabilities. The goal is to orient emergence so that we have some knowledge over what might happen.

CSO Design: Three Levels of Abstraction

The first step is still to plan and clarify the task. The difference is that the CSO-MIM process does not fully specify the environment and task requirements. Designers are still far from achieving comprehensively multi-functional and adaptive systems, but the CSO-MIM approach only calls for general task environment type. The designer would know of some expected functions and thus would identify certain functional capacities that might be desirable.

After the planning and clarifying task, there are three levels of abstraction to develop. The next abstraction level to develop is the individual cell model. This level of abstraction is still compatible with traditional design. This level defines the individual cells that will be used in the CSO system. The individual cell model will layout the scope of possible behavioral sets. Cells might be software agents, sensor nodes, or biological organisms. The COARM behavior set requires only a simple mechanical cell that can move in 2-dimensions.

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Planning with Uncertainty	CM: Cell Model	BM: Behavioral Model	MBM: Meta-Behavioral Model
✓ Specify some constraint over task environment ✓ Identify some functions ✓ Accept lack of knowledge	✓ Designer develops individual components of system	✓ No piece-by-piece functional decomposition ✓ Designer selects desired types of behaviors	✓ Asses relationship trends ✓ Develop behavioral heuristic ✓ Possible pre-deployment evolution

Figure 8: Meta-Interaction Model Process

The next step is to develop the Behavioral Model (BM) consisting of principal behaviors. The designer may pick behavioral models from previous experiences or develop new interaction sets. The designer has already accepted that the specific end behavior of the global solution will not be exactly defined, but using experience and knowledge can identify a set of local behavioral interactions. Example behaviors might be physical, communication and information interactions, or even learning actions. The COARM model is defined upon spatial movements.

And lastly, the Meta-Interaction level assesses the relationship trends in the simple interactive behaviors. These trends provide a heuristic for the designer to tune the system to perform functions. Secondly, they act as a guide for learning and evolutionary methods that can be implemented to facilitate the growth of the system. Using the insights from the MIM, the designer can identify interactive behaviors for different functions. Essentially, by controlling parametric variables, the system's mechanical implications can be manipulated. For well-known and studied systems such as Craig Reynold's Boids interaction model [12], the MIM has already been generally solved and developed [26].

The CSO approach pushes further into the design spectrum towards nature. The input for the design process has been relieved of the absolute deterministic constraint only requiring general definitions and classes. The output is not a single solution form but an amorphous system that can perform many functions. With further development, these systems will be able to grow and evolve to produce completely new structures and optimally specialize for certain tasks and environments.

It is important to note that the CSO Design Process does not eliminate the design engineer. This is not an automatic process that can work in the general case. It does not exclude the conventional approaches but still relies on the same basis of traditional design techniques and theory. It works in conjunction with established design approaches because it is a hybrid process combining principles from design theory with those from self-organization theory. This approach still relies on designer capabilities and intuition but not completely as it allows room for further natural developments. However, it does not reach a fully natural process as that is also not design. Natural process are fully reactionary while design approaches have specific functional objectives.

Example Application

To illustrate these abstract concepts, consider a small design example of the task application 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. Figure 9 shows a field where a 100 cell system has 5 large target objects to surround.

The CSO 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 space and deep ocean, or natural disasters like earthquakes and storms. The agent groups must be able to adapt to the situation without the need for a prior knowledge of the specific hazards that might be encountered. Figure 10 outlines the context for each level of abstraction as previously discussed.

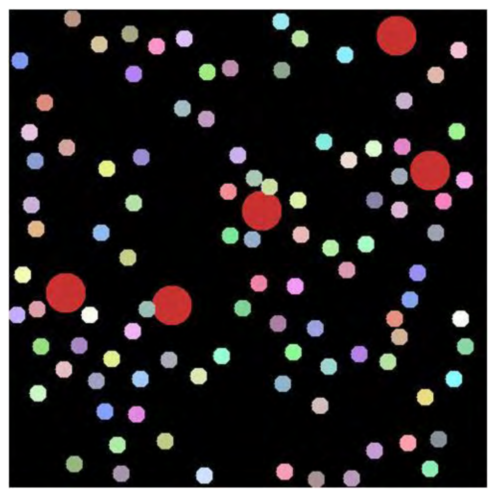

Figure 9: Search-and-Surround with 5 target objects

The search-and-surround mission requires function capacities of exploration and searching. These fall under a spatial and movement class of functions. The task will occur in a generally open environment they may have some hills and dips that create boundary limitations. There may also be possible enemy aggressors or other non-hostile entities that also exist in the environment. Because of the nature of the exploration and searching task, the target location is also unknown but only identified after discovery and verification.

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Planning and Clarifying with *Uncertainty*	BM
General Environment Definition: • Open terrain may have hills and dips. • Possible enemy aggressors • Unsure of target location General Function Class: • Movement, self propulsion • Particle net Uncertainties: • Necessary direction • Terrain layout • Hostilities	Requirements • Search net or separation distance • Continuous movement of search ➢ Use COARM Interaction Model
CM	**MIM**
• Simple mechanical cell • 2-D motion • Limited local sensor • Senses relative position and velocity • Sense foreign objects (boundaries) • Limited long-term memory (only MIM parameter weights)	• Preliminary tests and simulations • Justify working behavior • Behavioral heuristics • Introduce evolution algorithms • Finalize

Figure 10: Search and Surround CSO Design Process

This task requires the general function of motion. In a massive homogeneous system, the cells would be self-propelling creating a particle net in its exploration. The particle net also assists in the surround task as the second-phase task requires more than one particle to successfully discover the object, not just one. The main uncertainties are the environment layout although a generally expected terrain type is given. There is a huge uncertainty in the target location. Another uncertainty is in not knowing the possible dangers and enemy aggressors that might exist. However, the general function class is simply self-propelled movement.

Once the loosely defined requirements have been outlined, the designers next task is modeling, with the first phase in selecting a behavioral model. The interactive behaviors that may be required are maintaining a separation distance to create a particle search net and also continuous motion of search. To do this, the selection can focus on behaviors of synchronized motion and uncertain directions. The COARM model was selected and requires a very simple cell form for implementation, which aligns with the goals of using simple, non-intelligent agents. The intelligence of the system results from the combined global behavior.

And finally, the MIM for the selected BIM can be developed. For COARM, this has already been initiated in [26] and preliminary insights that outline the heuristic relationships were found. This information can be used for later growth implementations such as learning and genetic algorithms. As shown in [26] the designer can tune the parameter variables in order to accomplish the search-and-surround task.

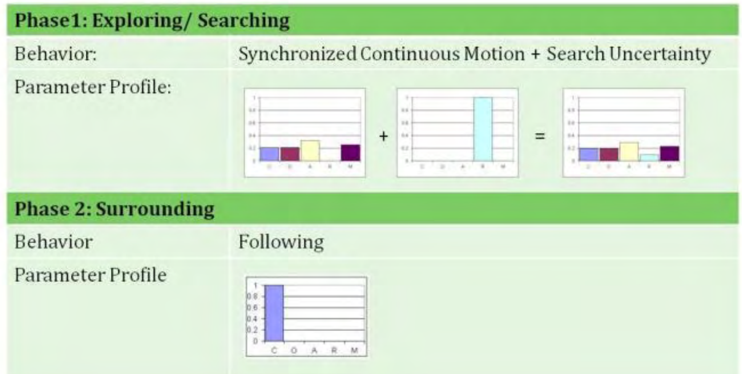

Figure 11: A COARM Profile for Search-and-Surround Task

As shown in Figure 11, for the search-and-surround task, the first function capacity is a combination of synchronized continuous motion and search uncertainty. Based on the trends, we can take a flocking profile and increase the random behavior in order to deal with the search application uncertainty. Phase 2 requires the function capacity of following. This requires an increased cohesion, so the cells requires a profile with greatly increased cohesion to the target objects.

Being able to tune the parameters to manage the system's multi-functionality shows the power of the meta-behavior model approach. Using the CSO-MIM approach, we can specify the top-down directive of search-and-surround but rely on the self-organizing of the system through behavioral interaction to accomplish the task..

CONCLUSIONS

In this paper we discussed a proposal for a CSO design approach. Our aim is to formulate this conceptual but practical model and validate it by observation of first simulation and then experimentation. The goal is to, not only introduce, but solidify a new paradigm in design theory toward complex systems and to harness the benefits provided by CSO. To make the design theory more universal requires bringing together as many domains as possible.

We discussed shifting the paradigm in design in order to extend the envelope of the design process towards complexity, a more "natural" way. We have presented the conceptual framework for the CSO design process. There is a fundamental shift from designing specific function capabilities to guiding emergent function capacities. With the results, we want to achieve a theory of design that is applicable in practice. The design process will become less dependent upon the single interpretation and capability of a designer but heed determinism for the sake of adaptability.

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The CSO design process is based on the self-organization and emergence processes in complex systems. In order to do so, it takes a Behavioral Based Design approach and is based on interactive behaviors, the fundamental property of complex systems. Using the Meta-Interaction Model based on behaviors, it aims to explore the space of collective behaviors that may achieve mechanical functionality. It also leaves room for growth and evolution after system implementation. While this element has not been as specifically discussed, the MIM provides design information and heuristics that can easily be applied by other research in control feedback, evolutionary methods, and learning approaches. Future research can combine these techniques such that the system can self-discover new behaviors and functional capacities.

Of course, the classical engineering approach may still be ideal when the environment can be well-defined along with the required function specification. CSO systems excel in complex environments containing unforeseeable circumstances because engineers cannot predict all the specific possible contingencies that may be encountered. CSO systems provide the adaptability in order to manage such uncertainties that classical systems cannot. On the other hand, CSO systems gain adaptability at the compromise of predictable determinism. Pure CSO systems may not be the optimal solution towards many problems, and a hybrid system combining deterministic hierarchical approaches with CSO methods may prove promising for further research. The given process already combines hybrid approaches, with the cell model still following a traditional design approach.

This paper has simply moved to extend the envelope of design and shift, not just towards artificial intelligence, but *artificial nature*. The CSO design approach may not be the one and only approach to extend the envelope, but it is a working one.

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