Hybrid Clumping: a Self-integration Basis for Complex Structures and Collective Dynamics

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***Abstract*—"Clumping" occurs when multiple entities come together or more generally get "closer" to each other in some physical or conceptual way (e.g., snowflakes, slime molds, yeast clusters, animal flocks, opinion-driven group segregation). We believe that such clumping tendencies provide a basic means for spontaneous self-integration among entities that were not "intended" for interaction and aggregation. It may precede more sophisticated coordination and self-integration. While nature-inspired self-aggregation has been widely studied for various engineering and control purposes (e.g., swarm robotics, clock synchronization, crowd dynamics), most applications only consider aggregating entities of a single type. In this paper, we concentrate on what happens to basic clumping (attraction among entities forming into swarms) when those entities' interactions are increasingly diverse. We provide a simple example that illustrates how swarms that start as homogeneous gradually change their structures and dynamics as they become heterogeneous. This is critical to autonomous cyberphysical systems as they venture out into the real world, where systems may opportunistically interact and integrate with other systems that are not the same as they are. Eventually, we aim to understand how much and what kind of similarity is required for what level of systems integration.**

I. Introduction

Integration among atoms, molecules and galaxies, or proteins, cells, and herds of animals, happens because of a large variety of interactions that bring individual entities together. Such interactions have generated increasingly complex atoms, stars, planets, galaxies, and, ultimately, a pathway for complex life on Earth [6]. Much research has studied grouping and group dynamics, e.g., swarms, predator-prey models, and organisms that form social aggregates. In this work, we emphasize how introducing variability in entity types and interactions changes the characteristics of their global integration. Our long-term interest is to identify fundamental principles by which dissimilar entities can usefully self-integrate, and to be able to apply these principles to the design of computational and cyber-physical systems that can self-integrate and then autonomously adapt to self-improve at both the individual and the collective levels. We use the term "clumping" to provide a generalization of the processes which lead to collective groupings.

We motivate our work by exploring "clumping" examples from various fields (sec. II). We then present a modest set of experiments to illustrate how hybrid self-integration may occur and the novelty it may bring. We employ a hybrid swarm simulation, where different mobile agent (*boid*) types interact with each-other via the same rules, yet different configurations (sec. III). In the Discussion (sec. IV), we interpret and link our experiments to the biological and computational examples presented in the Background (sec. II). We then discuss future work on how understanding the properties of heterogeneous systems can change how we approach integration at both the individual entity level and the global system-wide level.

This is important to SISSY systems [4] as we need to know how the individual actions of self-integrating entities impact (or not) the overall system of which they are becoming a part.

II. Cross-domain Background and Related Work

We discuss here some of what we know about the attractive forces in biological, cyberphysical, and information systems.

A. To clump or not to clump: a context-driven trade-off

We believe that a property we call "clumping" underlies the emergence of complex self-organizing [24] and self-integrating [4] systems. Clumping occurs when multiple entities come together, aggregate, or cluster, getting "closer" to each-other in some physical or informational way. In nature, this may occur spontaneously among entities that interact with each-other (e.g., via physical forces, behavioral tendencies or cognitive processes), within shared environments, forming various clumps, e.g., crystals, polymers, slime molds, animal flocks. While interactions in inert "clumps" may be fixed and context-driven (e.g., snowflakes), organic ones may use self-* functions to maintain coherence and goals across contexts.

In inert matter, the physics of phase separation predicts that larger structures should keep growing at the expense of smaller ones. In the Ostwald ripening process, larger crystals and droplets in a medium grow, while smaller ones dissolve (e.g., ice crystals growing in ice cream when stored for long times). Small structures typically grow until they trigger a curbing process, e.g., once raindrops get heavy enough they fall to earth. Yet, condensates in cells can maintain stable sizes for hours or days, due to various biological processes, e.g., the concentration-dependent size stability of monomer mixtures, due to merging-limited coarsening [8], similar to the parameter-driven structured swarming in our simulations.

Clumping tendencies provide basic means for spontaneous self-integration among entities that were not necessarily "in-

tended" for interaction and aggregation. There are many examples of such unintended clumping occurring among inanimate entities, e.g., raindrops built from smaller water droplets. Live individuals may feature innate sociability traits, yet these do not strictly dictate the integration processes they may engage with. This allows for a wide variety of aggregates to emerge when the attracting conditions (e.g., the right chemical messages or the right vocal signals from a herd) are met.

Emerging clumps may be symmetrical or amorphous (no particular structure), but may also differentiate into structures with more sophisticated functions (e.g., mushroom-shaped slime molds [33], snow-flake yeast clusters [25], v-shaped goose flocks). Complex dynamics and functions may also emerge along various clumped structures (e.g., a "biophysical scaffold" forming within a yeast colony, allowing fluid nutrient flows to reach all cells [25]; fluid-like dynamics emerging in moving crowds, which self-organize into lanes or move counter-clockwise in confined spaces and may create oscillations or waves at large densities [12]).

Reversibility is an essential feature of clumping, i.e., whether individuals are able to return to their independent states. Social aggregation of organisms is a reversible process, context-driven, with entities maintaining autonomy, and may happen without pre-planing of interactions or the end result. Social aggregates often form among similar entities engaging in symmetrical interactions, within confined spaces.

Nature-inspired social aggregation has been widely studied for various engineering and control purposes (e.g., robotic task selection, optimization, crowd dynamics) [7], [20], [18]. Yet, most applications only consider aggregates of a single entity type (e.g. Predator-Prey models employ multiple swarms to study collective intelligence reactions to threats, yet all individuals obey the same attraction, repulsion and alignment rules [37]; or, Multiple Swarm Particles Simulation Algorithms study the impact of environmental changes on the spread of pests and pathogens in crops, yet only using uniform particle interaction rules [1]). In contrast, we study the impacts of various heterogeneous interactions on the resulting clusters.

Cross-domain literature suggests that in living systems, social aggregation may bring advantages in terms of better efficiency and survival in challenging conditions, relative to individual autonomy. Predation avoidance may be enhanced by larger collectives (larger cell aggregates are harder to ingest); flocking animals achieve increased vigilance and cooperative defenses [28]. Harsh external conditions may also be better countered as collectives (e.g., algae aggregating into moving slime molds to find food [33]; emperor penguins huddling against extreme cold in the Arctic [38]; v-shaped bird flocks and cyclist teams improving collective aerodynamics). In social animals, there may be a trade-off between mutual support for raising offspring and competing for mating [28].

Clumping may also bring disadvantages, e.g., competition for resources, disease spreading, aggression and increased complexity management due to extra communication and coordination. These trade-offs may explain why most organisms today are unicellular [22], and why several multi-cellular organisms have "regressed" back to unicellular forms [30].

To optimize trade-offs, several species perform adaptive clumping, only aggregating in advantageous conditions (e.g., single-cell green algae *C. Reinhardtii* only aggregate in the presence of a predator (paramecium) [19]; amoeba *Dictyostelium* only form slime molds in case of food-shortages [19]; sheep only clump tightly when under threat [32]; Emperor penguins only clump in extreme cold events [38]).

The clumping size may also be adjusted as a trade-off: large penguin huddles split to avoid overheating at the center; animal groups spread-out or split into sub-groups to avoid local resource depletion; growing human organizations restructure to lower delays and information bottlenecks [15]. Finally, trade-offs in social aggregates may also be dealt with via internal dynamics that diminish individual disadvantages over time, e.g., continuous shifting of penguins between a huddle's center (warmer) and its periphery (freezing); regular position swapping within v-shaped bird flocks or car clusters to average-out draft resistance across different positions [14].

B. Clones vs. colonies: urgency, flexibility and complexity

Multicellularity occurs by either *cloning* (or division) of a single cell, or *aggregation* (or clumping) of multiple cells. Identical cells aggregate into "colonies" (slime molds); whereas cells from different species form "chimeras" or "symbionts" (endosymbiosis of mitochondria and chloroplasts in animal and plant cells, respectively). Multicellular individuals may also clump, either among the same species (sheep flocks) or different ones (lichen composed of algae, mycelium and bacteria; zebras and giraffes migrating jointly [29]). While the trade-offs stem from the actual composition, research has mainly studied aggregates of homogeneous entities and interactions [28], [34]. This vastly limits the collective organizations, functions and behaviors.

Conversely, in living systems, we often see the two kinds of self-integration (cloning and clumping) mixing across scales. Organisms grown via cloning (lower-scale) may clump with others (higher-scale), such as lichen's component organisms undergoing separate reproduction (cloning), then reintegrating (clumping). Clumping of genetic segments (lower), e.g., from viruses into multi-cellular DNA, may allow more differentiation within cloning organisms (higher) [26], [31].

Comparing the two integration methods highlights further trade-offs. Clumping may be faster and better adapted to opportunistic self-integration (in cell colonies it involves non-specific cellular binding; in animal flocks it only requires basic movement rules). It is also more flexible, as clumps may reverse to autonomous individuals (context-dependent). Yet, ad-hoc clumping may limit structural complexity, reproducibility and stability in various contexts (relative to DNA-based cloning). Clumping may also be subject to intrusion ("social exploitation"), as individuals may blindly bind to unsuitable entities (see [13], a study on yeast flocculation). Recognizing and selecting entities to bind to solves this issue, yet at a cost.

Finally, hybrid aggregates may also occur via individual differentiation within uniform aggregates. Such differentiation

was observed in unicellular colonies: slime molds of identical amoeba *Dictyostelium* cells differentiate into pre-stalk and pre-spore cells, forming a mushroom-like structure to facilitate reproduction [33]. Differentiation also occurs in social animals with the division of labor in ant colonies, and flocking sheep taking leader and follower roles [17].

C. Clumping in cyberphysical and information systems

Nature-inspired approaches were adopted for engineering more adaptable and resilient cyber-physical systems, including both clumping (swarm intelligence and robotics [5]; car platooning and clustering [14]; ant optimization algorithms [10]; self-assembling systems [2])) and cloning (morphogenetic engineering [11]; elastic clouds [23]). To the best of our knowledge, swarming research has focused on uniform self-integration, where all entities in a group interact in a single way, even when there are multiple groups. As noted above, we aim to explore the kinds of group structures and dynamics that may occur as entities start interacting in more diverse ways.

Aggregate computing [3] addresses self-integration in a top-down manner: it specifies the desired aggregate result (top), then infers the decentralized clumping algorithms (bottom) required to provide that result. While several top aggregates may be programmed into the same distributed platform, all entities contributing to a single result interact in one manner. It would be interesting to explore how an aggregate could be obtained via several kinds of interactions among entities.

"Classic" Software Engineering also supports dynamic component binding. E.g., Software-Oriented Architectures expose components via service interfaces and enable them to find and bind to each-other dynamically via special-purpose protocols. Message-oriented distributed systems further increase flexibility by skipping interface-matching constraints and merely requiring that participants employ the same middleware. In terms of coordination, centralized orchestrators are sometimes included to control execution ordering and avoid conflicts. Higher-level paradigms such as multi-agent systems rely on such technologies to achieve goal-driven self-integration [9].

A key limitation stems from constraining interactions to predefined protocols. This may prevent opportunistic self-integration among entities that were not designed for it. Middleware only enables communication, while integration semantics is exclusively assigned to message content and interpretation. We aim to explore how higher-level interactions may emerge opportunistically from more basic processes such as clumping. Interaction semantics lies at least partly in the interactions themselves, so online learning and evolution may also help in providing these capabilities.

Understanding the basics of spontaneous self-integration is necessary for autonomous cyberphysical systems, operating in real environments, where they may integrate with unknown, dissimilar systems. We aim to gradually define the kinds and degrees of similarity allowing systems to self-integrate in open environments. The hybrid swarm example illustrates opportunities that may be missed in current approaches.

Parameter	Role	Init. Val.
vision	boid visibility range	**50** [patches]
max-align-turn	max turning angle for boid alignment	**10** [degrees]
max-sep-turn	max turning angle for boid separation	**1.5** [degrees]
sep	minimum distance between boids	1 [patches]
trn	max turning angle for boid coherence	5 [degrees]

TABLE I: Initial Boid Parameter Settings: uniform parameters (bold) take the same value for all B_i; hybrid parameters (sep, trn) take a set value for B_0 and incremental values for $B_1..B_3$

III. Experiments

A. Illustrative Example: Hybrid Swarms

We examine the impact of diverse interactions on emerging clumping structures and dynamics with a simple hybrid swarm simulation using *boids* (mobile agents) based on a "classic" flocking model [27]. We show how novel structures and dynamics may occur as element interactions increasingly vary, how "too much" variation ultimately prevents swarm formation, and how the environment can influence the results. To simulate interaction diversity, we use multiple boid types, which follow the same interaction rules, yet with different configurations for each type. As the emerging swarms critically rely on differentiated behaviors, we conclude that the obtained shapes and movements do not arise by clumping uniform boids.

B. Hybrid swarm model

The simulation relies on a "classic" swarming model from the models library of NetLogo, an agent-based modeling platform [36], [35]. We introduce integration diversity by defining four types of boids ($B_i, i = 0..3$), which we differentiate via the values of two self-integration parameters:

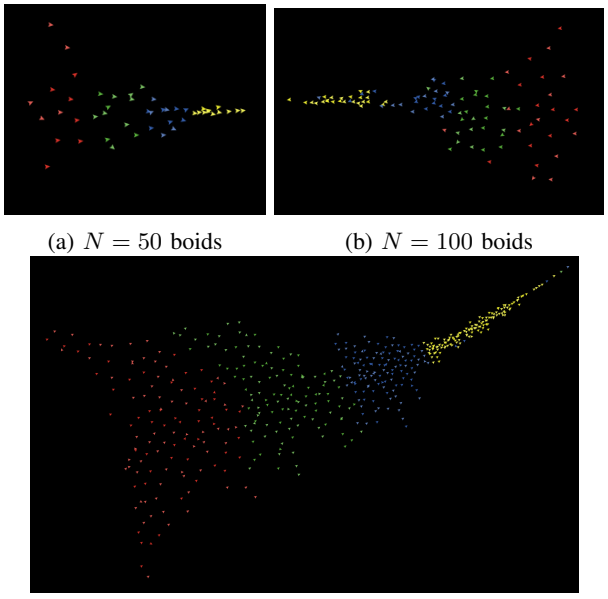
- minimum separation (sep): the smallest distance allowed between boids;
- maximum coherence turn (trn): the widest angle change allowed to ensure direction coherence among boids.

Different parameter values are assigned across the four boid types, as in equations 1 and 2. Here, sep_{init} and trn_{init} are the initial values assigned during setup, via the graphical interface; amp is a differentiating factor between boid types.

$$sep_{B_i} = sep_{init} + (i * amp) \tag{1}$$

$$trn_{B_i} = trn_{init} + (i * 2 * amp) \tag{2}$$

This implies that boids of the first type (B_0) take the initial setup values (sep_{init}, trn_{init}) and boids of the other types (B_1,B_2,B_3) take increasingly larger values, with the increment modulated by their type index (i) and the amplifier (amp). Table I lists initial value settings for all parameters: "uniform" (bold italic), taking the given value $\forall B_i$; and "hybrid" (italic) taking the given values for B_0 and calculated values for other $B_i, i > 0$. The world is toroidal and measures 150 x 90 patches in the default case. Time is simulated in discrete steps.



(a) $N = 50$ boids (b) $N = 100$ boids

(c) $N = 500$ boids

Fig. 1: Layered triangular swarm structure emerging from four boid types B_i ($i = 0..3$) with different sep values ($sep = i$); same $trn = 5$; for different swarm sizes, $N \in \{50, 100, 500\}$. B_0 boids are yellow; B_1 blue; B_2 green and B_3 red.

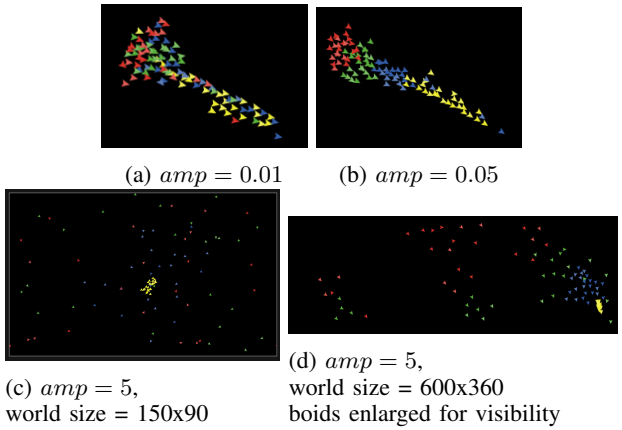
C. Experiments & Results

1) Differentiated structures: Simply differentiating boid types via their sep parameter, with $amp = 1$, gives rise to a layered, triangular swarm shape (Fig. 1). Boids with the smallest sep value (B_0, in yellow) are mostly at the front; followed by subsequent layers of boids with larger sep values (B_1, blue; B_2, green; B_3, red). This structure persists for various swarm sizes, e.g., $N \in \{50, 100, 500\}$ in Fig. 1.

The fact that boid types with smaller sep values form narrower swarms is intuitive. The fact that they tend to separate into layers, ordered by their width, may seem more surprising. This occurs as boids with larger sep values travel more sideways, hence advancing slower and lagging behind; while angle coherence maintains overall swarm coherence.

2) Viable integration diversity: Fig. 2 demonstrates the effects of changing the difference between the minimum separation sep used by each boid type (i.e., by varying amp, and using eq. 1). All simulations use $N = 100$ total boids, with the default parameters in Table I. Structured swarm formation begins to manifest even at quite small amounts of differentiation between the boid types: $amp = 0.01$ in Fig. 2a, but this case requires a long time to develop. Increasing amp to 0.05 (Fig. 2b) produces a fully layered swarm, similar to Fig. 1b, yet with a narrower triangle base (due to smaller sep values).

As amp, and therefore sep, are increased, the width and length of the structured swarm continue to increase. Eventually, the limited size of the toroidal world causes the swarm to "catch up" with itself as the swarm front overlaps the diffuse tail. The result is a loss of swarm structure. The boid types with smallest sep (yellow and blue) remain in a diffuse swarm, moving together, while the other types are no longer part of the swarm (Fig. 2c). Increasing the world size by a factor of 4 (Fig. 2d) shows that the swarm maintains its basic structure again, as there is no overlap, but with the boid type with the largest sep no longer completely integrated. Thus, in confined environments such as our toroidal spaces, boids are forced into interactions which perturb the swarm and its structure. This can lead to recurrent cycles of organization and disintegration, partial integration, and other complex behaviors.



(a) $amp = 0.01$ (b) $amp = 0.05$

(c) $amp = 5$, world size = 150x90

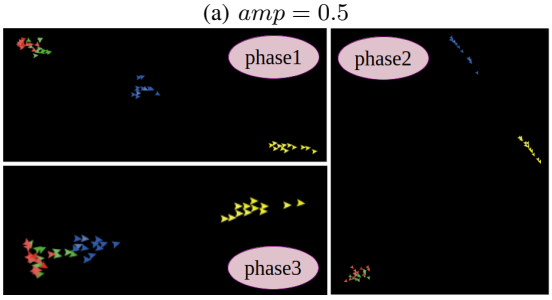
(d) $amp = 5$, world size = 600x360 boids enlarged for visibility

Fig. 2: Effect on swarm formation of varying the difference between the boid type's sep_i parameter via the amp parameter

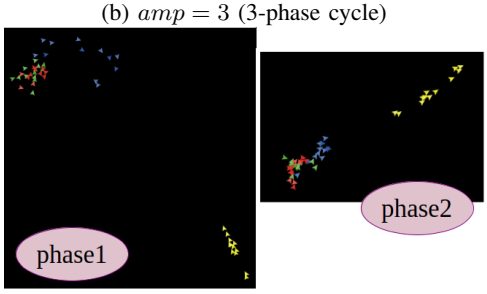
3) Distinct swarm dynamics: Varying the trn parameter, while keeping sep constant, leads to various swarm formations and dynamics. The limited toroidal space further leads to interference between swarms, which merge and split through cyclical phases (Fig. 3). We vary the differences between trn_{B_i} via $amp \in \{0.5, 3, 5, 10\}$ as in eq. 2. For relatively small differences ($amp = 0.5$) boids clump into a layered swarm (Fig. 3a). This outcome is like the one generated by varying sep, yet with no triangular shape since sep is constant.

Increasing the difference between trn values ($amp = 3$) splits the swarm into sub-swarms that feature different dynamics and change periodically (Fig. 3b). In one phase, three swarms differentiate and follow each other at a distance (cf. phase1 in Fig. 3b). The leading swarm contains boids with the smallest value (yellow, $trn = 5$), the second with medium values (blue, $trn = 11$) and the third with larger values (green and red, $trn = 17$ and 23, respectively). The following phase occurs as the third swarm lags behind and moves as a separate swarm (cf. phase2 in Fig. 3b). Because of the limited toroidal space, this isolated swarm crosses the two other swarms and, for a while, attaches to them (cf. phase3 in Fig. 3b). In time, this third swarm lags behind again, detaching from the other ones and getting back to the initial dynamics (cf. phase1 in Fig. 3b). Across the three phases, the dynamics of the third swarm (green & red) depends on its proximity to the other swarms (yellow & blue): boids turn less, move faster and organise into layers when following the other swarms (phase1 & 3) relative

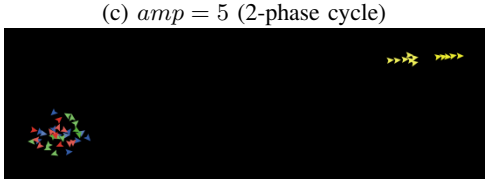
(a) $amp = 0.5$



(b) $amp = 3$ (3-phase cycle)



(c) $amp = 5$ (2-phase cycle)



(d) $amp = 10$

Fig. 3: Effect of changing the maximum coherence turn parameter ($trn \in \{0.5, 3, 5, 10\}$), with $sep = 1$ for all boids ($N = 50$) and other parameters given in Table I

to when moving separately (phase 2).

Further increasing the variation ($amp = 5$) leads to a different dynamics (Fig. 3c). It creates two independent swarms (phase1): one moving (yellow, $trn = 5$); and the other more stationary and cloud-like (blue-green-red, with $trn = 15, 25, 35$, respectively). When the moving swarm crosses the cloud-like one, the latter follows it for a while (phase2); then lags behind and separates again (phase1). Finally, higher variation ($amp = 10$) leads to two distinct swarms, one moving and one cloud-like, that never integrate, even when passing through each other (Fig. 3d).

4) Bidimensional variation of clumping: Varying both parameters (sep and trn), with $amp \in \{0.5, 3, 5\}$, $N = 50$, leads to further structural and behavioral diversity (not shown, due to space limitations). For small variations ($amp = 0.5$), we obtained a layered shape similar to the one formed when only varying trn (Fig. 3a). Compared to the case where only sep varied, boids in the back layers turn more abruptly and align behind each other, creating a more linear shape.

Larger variations ($amp = 3$) lead to two distinct, persistent groups: 1) a moving swarm (yellow, smallest sep values); and, 2) a stationary, cloud-like swarm (green&red, largest sep values). The dynamics of boids with intermediary values (blue) change over time: following the moving swarm (yellow); being trapped by the cloud-like swarm (green & red); or forming a separate moving swarm. Notably, boids in this intermediate group (blue) may all feature one of the behaviors above, at any one time; or split into sub-groups, each with a different behavior. These cycling structures and dynamics feature similarities with the previous cases (when only one of the two parameters was varied), while also featuring new behaviors. Further increasing variation ($amp = 5$) produces similar results, yet the cloud-like swarm becomes more dispersed and sometimes splits. These observations show the richness of integration behaviors when varying several clumping dimensions.

IV. Discussion

Our experiments show that even simple models can generate more structured collectives and richer dynamics when introducing some variation in self-integration processes, instead of assuming uniform processes. While keeping the same kinds of basic interactions among all boids, we diversified boids into four types by varying the configuration values of two basic processes – minimum separation and maximum turning angle.

We experimented with varying these parameters within different ranges, both separately and combined. Varying the minimum separation between boids added a layered triangular structure relative to the one obtained from uniform boids. Varying the maximum turning angle led to a layered structure without triangular shape and showed the potential to generate swarm differentiation and rich inter-swarm dynamics including cyclic behaviors. Varying both parameters combined some of the separate features above, generating further kinds of structures and dynamics. In all cases, the range of variation across boid types was an important factor. Smaller variations led to more tightly connected swarms, larger ones led to diverse shapes and movements, and even larger variations led to even less organization.

The limited size of the world was another key factor, forcing differentiated portions of the swarm to remix after structuring. The obtained dynamics were strongly influenced by a reference group (yellow), which always took the same initial parameters (cf. Table I), leading to a relatively tight, moving swarm.

V. Early Conclusions and Future Work

Even though our experiments are relatively basic, these findings confirm our intuition that variations in entity self-integration can produce a richer range of emerging structures and dynamics than uniform integration. We also note that the nature of the environmental context can have a significant effect on these interactions, providing another rich area for understanding and engineering particular types of behaviors.

We intend to explore further variations in boid behaviors; as well as investigate these effects in other applications (crowd management). Ultimately, we aim to develop a conceptual framework for clumping and the more complex self-integration

processes it may support. Clumping dimensions ("getting closer") may be physical (e.g., location, timing, temperature, speed) or conceptual (e.g., parameter value, model structure). Information-driven clumps may include self-clustering conceptual spaces [16], self-assembling agent systems and opinion-driven bubbles.

Clumping may be combined with other self-* processes to provide more complex collective functions. Clump size assessment combined with preferential attachment may create scale-free networks (e.g., "rich get richer"). Combined with adaptive behavior it may enable collective decisions (e.g., baboons determining where to spend the night by comparing the sizes of opinionated groups [21]).

Exploring the ramifications of hybrid interactions in these clumping-driven domains may bring novel contributions to the hard problems involved in developing complex self-* systems operating in open, unpredictable environments.

The implications for complex autonomous cyber-physical systems (e.g., robotic swarms, space systems) are also important, with many computational processes resembling "social aggregation". Programs connect temporarily, provide information or services, and then return largely unchanged, except for some new learning or recorded data.

However, many questions remain. When should we change a component to make it fit within another system? When should such changes be permanent and when flexible (e.g., varying sensors and actuators)? What extra capabilities and knowledge would a self-integrating system need to change itself? How would its self models change to allow these alterations? How should components decide when and with whom to self-integrate and when to disconnect?

We believe that our initial study opens a broad range of rich research opportunities in hybrid SISSY systems and that this initial paper will serve as a starting point for a SISSY discussion on adding more diversity to our integration approaches and building better methods for mapping between the adaptations of individual entities and their impact on the wider systems of which they are a part.

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