The Complexities of Computer-Supported Collaboration

Mark S. Hancock
University of Calgary
2500 University Drive NW
Calgary, AB, Canada
msh@cs.ucalgary.ca

Sheelagh Carpendale
University of Calgary
2500 University Drive NW
Calgary, AB, Canada
sheelagh@cs.ucalgary.ca

ABSTRACT
We introduce the idea of considering computer supported collaborative work as a complex adaptive system (CAS). In other disciplines, such as physics, biology and ecology, the idea of a CAS has proven useful in explaining a wide variety of phenomena. We define a CAS and then describe how CSCW fits that definition. We demonstrate that the concepts in CAS theory can be applied to help understand computer supported collaboration and provide examples of catastrophe and chaos in physics showing how they can be paralleled in CSCW. The implications of the application of CAS theory to CSCW include greater insight into the computer supported collaborative process and inform both evaluation methodology and design of applications.

Categories and Subject Descriptors
H.5.3 [**Information Interfaces and Presentation (e.g., HCI)**]: Group and Organization Interfaces – Collaborative computing, Computer-supported cooperative work, Evaluation/methodology, Theory and models

General Terms
Design, Human Factors, Theory

Keywords
Complex Adaptive System, Collaboration, CSCW

1. INTRODUCTION
In themselves, the dynamics of collaboration are complex. In addition, while using technology to augment these collaborations may increase collaborative possibilities (such as making it possible to work together across distances), the actual collaboration dynamics remain difficult or perhaps in some cases become more challenging due to new factors such as changing levels of mutual awareness [9, 11]. The question we explore in this paper is not whether group collaboration is complex in the normal use of that term but whether it might be useful to consider it as a complex adaptive system. The basic components of a complex adaptive system seem applicable in that collaborative groups change and adapt to changing conditions over time and in that the people who compose these groups are complex in themselves and are also adapting to the changing conditions. We explore the question of whether light can be shed on computer supported collaboration by considering it as a complex adaptive system.

One possibility where the ideas being developed as part of CAS theory may prove useful is in the modeling and evaluation of collaboration dynamics. The fact that evaluating computer supported collaboration is difficult has been stated with increasing frequency over the last few years. This difficulty has prompted papers [7, 8, 21], workshops [13], and has resulted in many types of frameworks and guidelines [28, 24, 21]. In fact, discussions about the failure of standard statistical practice to properly explain collaborative behaviour and validate good interface design pervade the literature in this area [7, 8]. This has led to characterizations of behaviour such as the mechanics of collaboration [24], development of guidelines for heuristic evaluation [3], as well as more specific guidelines such as those provided by Scott et al. [28] for co-located collaborative work on tabletop displays. The theme among these discussions is a decomposition of collaboration into constituent parts. While these decompositions have expanded our understanding of the collaborative processes and have been useful for designers, they also indicate a lack of an overall or holistic understanding of the collaborative activity in the computational environment.

These collaboration factors do not exist in isolation and do not always have mutually positive effects. For instance, the tradeoff that exists between individual performance and group awareness, noticed by Gutwin and Greenberg [9] has now been empirically confirmed [11]. Exploration of this tradeoff shows that support of group awareness can come at the price of individual performance and vice versa. Thus, the advice necessary for designers is not that these environments should support group awareness, but that they should consider how to balance these two important parts of collaboration in their application. This holistic understanding can then help the designer to develop the technology according to the particular needs of the application.

Since decomposition into component parts may not always help us understand how to proceed, we need to consider how to develop a more holistic view of collaboration. In parallel with our dilemma, in many other sciences, both natural and social, there exist branches of research that are focused

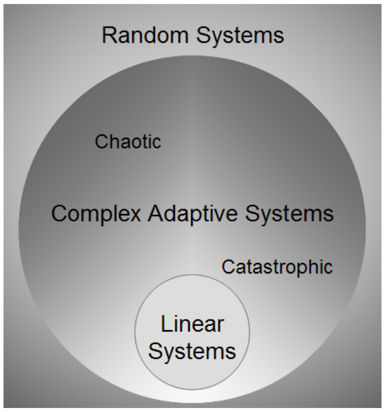

Figure 1: This diagram relates linear, complex adaptive, and random systems. The diagram itself is not to scale. There are so many more complex adaptive systems than linear systems that, if this was to scale linear systems would be less than a pin point.

on the need to develop understanding of systems that do not respond well to decomposition. These complex adaptive systems (CAS) need to be studied as a whole. In this paper, we show that the descriptions, definitions and terminology used in studying CAS in other sciences can also be used for computer supported collaboration and to provide insight into both the evaluation and design of technology that supports collaboration.

Scientific research is currently developing methods for the study of non-linear systems through use of complex adaptive system theory. This research shows that linear systems are a small part of a much larger spectrum of dynamical systems including complex adaptive systems and random systems (see Figure 1). Activities in complex adaptive systems are neither random nor linear but exhibit complex patterns that depend highly on the history and context of the system itself. Some of the characteristics of these patterns are becoming better understood [14]. We suggest that computer supported collaborative work fits more naturally in this larger spectrum as a complex adaptive system.

2. EVALUATING CSCW

Due to the continuing challenge of evaluating collaborative systems, several models or frameworks have been put forward. Since we are suggesting including the complex adaptive system model as also useful in this regard, in this section we briefly review the existing models and end by noting successful application of CAS theory to the study of small groups in behavioural science and its application in other areas on computer science. There have been many attempts to explain behaviour in CSCW. Because of the difficulties involved in describing this behaviour, both evaluation and design of collaborative applications have been recognized as difficult problems [7, 8]. This difficulty has been the driving force for a wide variety of evaluation frameworks and design guidelines.

Neale et al. [21] discuss three types of CSCW frameworks: methodology-oriented frameworks, conceptual frameworks, and concept-oriented frameworks. *Methodology-oriented frameworks* describe the different methods and experiments used to evaluate CSCW applications. McGrath [18, 19], identifies a variety of experimental methods available for the evaluation of groups. He argues that multiple methods must be used to triangulate the truth or falsity of a hypothesis and that a single study is insufficient to simultaneously achieve precision, realism and generalizability. Pinelle and Gutwin [22] classify the methods that were used to evaluate a variety of CSCW applications by the setting (naturalistic vs. controlled) and manipulation technique (rigorous vs. minimal).

Conceptual frameworks [21] describe the fundamental properties of collaboration that should be evaluated. One such framework is the mechanics of collaboration [24, 10]. The mechanics decompose collaboration into fundamental components including explicit communication, consequential communication, and coordination of action among others. These mechanics have led to low-cost evaluation methods such as heuristic evaluation [3] and design walkthroughs [23]. Scott et al. [28] present a similar decomposition for co-located collaboration. They identify the need for "(1) natural interpersonal interaction, (2) transitions between activities, (3) transitions between personal and group work, (4) transitions between tabletop collaboration and external work, (5) the use of physical objects, (6) accessing shared physical and digital objects, (7) flexible user arrangements, and (8) simultaneous user interactions". They suggest that tabletop applications could be evaluated by their ability to support these needs.

Activity theory has also been suggested as a possible conceptual framework in which to evaluate collaborative applications [20, 32, 21]. This approach decomposes collaboration into a hierarchy of activity. The central level of the hierarchy is made up of *actions* which occur when the higher-level *goals* become realizable and are composed of automatic processes called *operations*.

Concept-oriented frameworks [21] isolate a particular aspect of collaboration and provide advice about how to measure the success of an application in terms of that aspect. Participatory design methods have been extended for groups [26], methods exist for analyzing interpersonal awareness [33], and breakdown analysis [12] can be used to describe problems in group dynamics. Mandryk and Inkpen [17] describe how to measure variables such as fun and excitement in a co-located setting. These measures use physiological indicators, such as galvanic skin response and heart rate to quantify these previously qualitatively measured variables.

In summary, methodology-oriented frameworks provide advice about how to conduct evaluations, conceptual frameworks indicate what it is important to measure and concept-based frameworks describe how to measure factors that have been deemed important. In this paper, we describe how a well understood theory, CAS, can explain the interactions between the identified significant concepts and in doing so can help explain why and when different types of methodological approaches may be useful.

While use of CAS theory may be new to CSCW, it has been usefully applied in the development of managerial and organizational systems. Tan et al. [30] explain how a hospital system can be better managed when viewed as a CAS. Ramnath and Landsbergen [25] show adaptive systems can be used in strategic planning for city governments.

The idea of considering collaborative activity as a complex adaptive system is also not a new idea in the behavioural sciences. Arrow et al. [1] describe small groups as a CAS. Arrow et al. [2] provide a review of how a temporal perspective has been used to good effect in the behavioural sciences to describe how time and change affects the dynamics of a group. The focus in this realm of literature is somewhat different than that in CSCW literature. From the behavioural science perspective, the problems are specific to understanding the actual behaviour of the group. For instance, behavioural scientists explore how groups form, how decisions are made, and how groups learn. In CSCW, the element of technology plays a more important role. An important part of the benefit of understanding collaboration is to help inform the design of technology to support group activity. The purpose of this paper is to demonstrate how understanding CSCW as a complex adaptive system can help to inform the design of computer applications that support collaboration.

3. COMPLEX ADAPTIVE SYSTEMS (CAS)

In many other disciplines, including biology, physics and ecology, it has been noticed that simple dynamical systems can exhibit complex behaviour that arises from how the components of the system interact with each other. A dynamical system that exhibits this type of behaviour is called a complex adaptive system (CAS). We start by briefly explaining the terminology used to describe CAS.

3.1 CAS Terminology

A *dynamical system* is composed of two parts [4]: (1) an *environment* in which the action takes place, and (2) a *vector field* that defines the rules of motion. The system begins at an *initial state* and follows a *trajectory* which has an end point called an *attractor*. In many dynamical systems, the transition from initial state to attractor occurs rapidly, so observations of the dynamical system are typically when the system is on or near an attractor.

There are three types of attractors: *fixed-point*, *limit cycles*, and *strange attractors*. A fixed-point attractor occurs when the final state of the system is a fixed point and depends only on the initial state. A dynamical system can have many fixed-point attractors. A limit cycle occurs when the system tends toward a periodic orbit. The most common and complicated attractor is the strange attractor. The structure of a strange attractor is made up of unstable periodic orbits and aperiodic paths.

3.2 Properties of a CAS

To help identify when a dynamical system is a CAS, it is useful to consider the properties of a CAS as described in ecology. Kay et al. [14] describe the properties of a CAS from an ecological viewpoint:

Non-linear - the system cannot be understood by decomposing it into pieces which can then be added or multiplied [s2]together.

Holarchical - the system is nested within systems made up of systems. It cannot be understood by focusing on one level alone. Understanding comes from multiple perspectives of different *type* and *scale*. A holarchy consists of interacting levels that do not necessarily have a set ranking.

Self-organizing - the system is non-Newtonian. The system is composed of many agents that can each affect their local environment. These agents self-organize based on positive and negative feedback. This self-organization can result in emergent and surprising properties.

Window of vitality - the system is complex, but not too complex. There is a range within which self-organization can occur. The system strives for an optimum, not a minimum or maximum.

Dynamically stable - there may be no equilibrium points for the system. Stability may only be observable when the system is considered over a long period of time.

Multiple steady states - there is not necessarily a unique preferred system state. Multiple attractors may be possible in a given situation. The history of the system may determine in which of these attractors the system currently is.

Catastrophic and Chaotic behaviour - the system is characterized by bifurcations, flips, and an inability to forecast and predict. These two properties are discussed below in greater detail.

3.3 Collaborative Activities as a CAS

In this section we explain collaboration using CAS terminology. The *environment* of this dynamical system is composed of: the technology and tools available; the composition and structure of the group; and the group constraints such as space, time, and distance. Perhaps a good way of thinking about this is that it includes all the communication channels available to the group members. This would include usual person-to-person communication channels such as verbal and body language and all the factors that contribute to each member's awareness of the others' actions and intentions. It also includes the communication channels made available by the technology in use whether that be video conferencing, whiteboards or smart boards and/or mobile devices. Largely, the agents in this CAS are the people involved. However, it is possible that some factors in some software may also act as agents.

The *vector field* is the set of all factors that affect an individual agent's beliefs over the course of the collaboration. These include explicit factors such as knowledge of the subject of the collaboration, point of view on the subject, stated objectives, recognized outside pressure, time commitments, and public relationships with other collaborators. They also include implicit factors such as personal intentions, private relationships with collaborators, and unspoken outside pressure.

The *initial state(s)* of the system are the properties of the members of the group. This includes such things as their familiarity with each other, their individual abilities and emotional states, among many other variables. The state of the dynamical system will be observable as the group dynamic or strategy at a given point in time. This state will likely be on or near an *attractor* of the dynamical system from the point of view of the observer. Attractors can include group dynamics such as the fixed-point state of silent work, a limit cycle of periodic turn taking, and strange attractors such as brainstorming activities.

Next we describe how this dynamical system exhibits the properties attributed to a CAS.

3.3.1 Non-linearity

While at least some of the variables in individual work are reasonably well understood, the variables used to describe success in collaboration do not follow linear relationships. When considering computer supported individual work, due to physiological properties of humans, individual performance can sometimes be measured and predicted using classical statistical analysis. Speed and accuracy have been shown to fit a mathematical model called Fitts' Law [5], which can be demonstrated using *linear* regression. At the individual level, this model may be sufficient to describe performance most of the time, but in collaborative activity, performance does not often follow this linearity. Group work often incorporates interruptions for a variety of activities, including group discussions, sharing of information, and coordination.

The main point of non-linearity is that in general, it is not possible to understand collaboration by decomposing the system into multiple instances of a single person using technology. Research in human-computer interaction provides much more insight into the design of interfaces for single users and how changes in the interface will affect interaction. Thus far, it has proven difficult to extend this insight successfully to collaborative technology. This failure may be caused, at least in part, by the non-linearity of collaboration.

3.3.2 Holarchy

There are multiple interacting levels or systems that make up a collaboration. Each individual is a system onto him or herself, therefore at one level, there are the physical actions of each individual at each point in time. At another level, the main-group and sub-group strategies arise from coordination between individuals. There are also the group goal(s) of the collaboration that set the group actions in a bigger society. Although it is helpful to consider each level, they cannot be individually understood and must be considered inside the context of the other levels. This holarchy is distinguishable from a hierarchy in that there is no implied ordering and the levels do not stand on their own.

3.3.3 Self-organization

The agents within a collaborative environment are primarily the members of the group. These members make decisions based on observations they make about the system. The local environment of each collaborator is the entirety of information available to them within their perceptual realm. Based on positive and negative feedback from their local environment, these agents then make local changes. Due to these local changes, emergent properties of the system occur, such as coordination, communication, and sometimes conflict.

3.3.4 Window of vitality

For a successful collaboration to exist a limited range of complexity must be maintained. That is, too low a level of complexity will limit creativity and buy-in, and too high a level of complexity may not allow objectives to be met in a reasonable time. It is also possible for the complexity to reach a destructive point. For instance, if group members cannot speak the same language or the technology is not usable, it may be impossible to coordinate or communicate.

3.3.5 Dynamic Stability

It is typical in collaborative environments for the activity to frequently shift from one state to the next without settling into any equilibrium – a balanced, unchanging or periodic state. Attention shifts easily, periods of silence are interspersed with intermittent periods of frequent chatter, spatial territories are established and re-established [27], and seating patterns are often altered. The state of the system at a particular moment is temporally dependent and will require knowledge of the history of the situation [21].

3.3.6 Multiplicity of Steady States

To demonstrate the existence of multiple steady states, let us consider the communication variable *amount of talking*. Group members might reach a state of no talking once they have devised a plan of action and are in the process of carrying out that plan. On the other hand, they may have achieved a different steady state in which only one group member is talking (currently has the floor). This steady state may occur if one user has decided to present the results of their individual work to the group. Note that it is sometimes the transition between these steady states (when the group members must coordinate to determine who speaks) that is most interesting and can help to inform good design of the technology that supports this interaction. Steady states such as these exist for other variables in the environment.

3.3.7 Catastrophic and Chaotic Behaviour

We caution the reader not to confuse the CAS terms catastrophe and chaos with the colloquial usage of these words. In a CAS, a *catastrophe* is simply a sudden change or discontinuity within a dynamical system. The term *does not* imply that the system has undergone any profound or disastrous event, it simply implies a sudden change that cannot be described linearly. For instance, collaborations often contain periods of coordinated group activity and of parallel individual activities designed to achieve a group goal. The switch between these two types of collaboration tends to be sudden, often prompted by a single comments or request. Similarly, a chaotic system *is not* one without order. In fact, it explicitly does not contain random actions but is composed of actions that cluster into complex patterns. It can be understood and it can result in satisfying outcomes. We introduce these terms because they can help in the understanding and evaluation of non-linear systems.

In collaboration, behaviour described by the CAS terms, catastrophe and chaos, is not only present, but appears to be the norm. In the following sections, we describe how catastrophe and chaos are observable in collaborative environments.

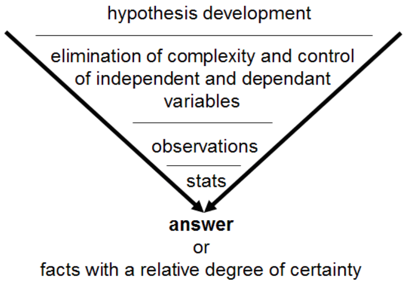

Figure 2: A simple schematic of the normal scientific experimental process.

3.4 CAS and Evaluation of CSCW

In the field of human-computer interaction, evaluation of interfaces typically involves controlled experimentation. The normal scientific method involves (a) the development of hypotheses, (b) the elimination of complexity and control of independent and dependent variables, (c) observations, and (d) statistical analysis (see Figure 2). Following this procedure, the scientist can be relatively certain of the verity of the starting hypothesis. Science has greatly benefited from the success of this method and because of this procedure we have obtained a vast amount of scientific knowledge.

This procedure has proven difficult to apply to the advancement of knowledge about complex adaptive systems. Discussions about this difficulty are prevalent in other sciences [14, 1]. In particular, presence of interlocking activities and the general non-linearity of the collaborative processes can make the normal elimination of complexity and control of independent and dependent variables counterproductive. The idea to observe simpler, more manageable subsets of the process is appealing, but the non-linearity of a complex adaptive system implies that the parts of a system cannot simply be added together and, as a result, the system cannot be fully understood by studying the components in isolation. That is, the group dynamics cannot be understood by combining the individual properties of the group members. Moreover, the behaviour of each individual cannot be understood without situating that behaviour within the context of both the group and the beliefs and knowledge obtained from their experiences in society as a whole.

The response in many sciences has been to undertake studies that differ in both formulation and results. The experiments in these sciences are formed so that they maintain the complexity of the full system. These systems may be a simplified version of the full system, but care is taken to ensure that the key elements of the complex system are still present. While variables of interest may be monitored individually, this monitoring takes places in the context of a system that exhibits the necessary complexity. The results of these studies do not tend to provide definite answers, but rather generate an increased understanding and/or insight into the system (see Figure 3). A trend towards these types of studies is already apparent in the adoption of ethnographic methods in CSCW. Examples of these types of studies are naturalistic [22] and observational [19] studies.

An alternative approach to understanding this complexity

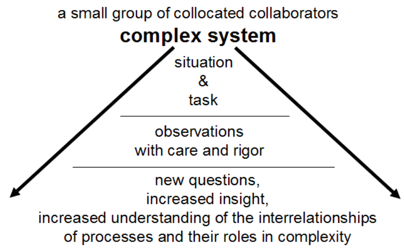

Figure 3: A schematic of observational study process. The results are relatively "soft" facts but can lead to greater understandings.

is the use of simulators. Instead of reducing the full system to a more understandable system, a simulator approaches the problem from the opposite direction. The agents of the system are initially modeled to be as simple as possible and are slowly made to be more complex until the simulated system exhibits emergent properties that resemble those in the full system. These systems similarly result in insight and understanding rather than definitive answers. McGrath [19] also describes simulators as a method that simultaneously maintains some realism and some precision (at the cost of generalizability).

4. RECOGNIZING A CAS

In this section we draw parallel descriptions of CSCW behaviour and the behaviour of a CAS from physics. Keeping the examples from both CSCW and physics simple, we show how non-linear changes in group awareness can be explained with catastrophe theory using the simple physics example of beam buckling. For our second collaboration example we take the characteristics of real collaborative tasks such as air traffic control, brainstorming sessions, and hospital care, and generalize them to multiple people creating an ever changing puzzle. The possibilities of multiple different outcomes can be described in terms of chaos theory and paralleled in physics with the behaviour of a water wheel. These descriptions are included to provide the reader with the tools to identify the types of behaviours that are typical to complex adaptive systems so they can use these theories to explain phenomena that they may observe in collected data.

4.1 Describing Non-Linear Changes

In order to use catastrophe theory to describe non-linear changes in group awareness, we first explain the physics example, beam buckling, and use it to help define common terms used to describe catastrophe. Then in Table 1 we draw a comparison to non-linear changes in group awareness.

4.1.1 Physics Example: Beam Buckling

Catastrophe theory has been shown to be more effective when used to provide descriptions [4] rather than predictions [35, 15]. For instance, it can provide a mathematical description of an entire set of fixed-point attractors of a dynamical system. The mathematical description is a function that maps the n-dimensional control space (input) to the m-dimensional state space (output). René Thom's Classification Theorem [31] proves that any dynamical system that is catastrophic has a canonical description. An example is the *cusp catastrophe*, which provides a description of the possibles states for any system with $n = 2$ and $m = 1$. [s2] One example of a catastrophe in the physical world occurs when force is applied to a beam of wood (see Figure 4). This example is adapted from Casti [4].

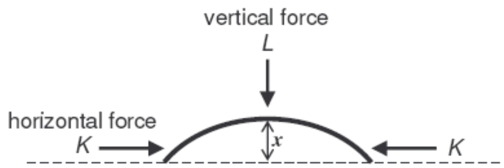

Figure 4: A buckling beam of wood.

The state space variable x represents the vertical displacement of the beam from its resting position. The control space, in this case, is the forces applied to the beam. The first force, K, is applied to the ends of the beam along the horizontal. (1) When $K = 0$, the beam will stay flat. When a force is applied ($K > 0$), the position of the beam will initially not change, but once a threshold value is reached (2), the beam will suddenly buckle either upward or downward. A force, L, can then be applied in the vertical direction (3). A negative (upward) force applied to a downward-buckled beam will initially cause the beam to gradually flatten and once a threshold value of L is reached, will suddenly cause the beam to buckle upwards (4). A negative force ($L < 0$) will similarly cause the beam to buckle downward again (5). The entire set of fixed-point attractors of this dynamical system can be drawn as a surface above the two-dimensional control space (see Figure 5).

4.1.2 Properties of a Catastrophe

The properties of this and any other catastrophic dynamical system provide insight into how one might identify a situation that can be explained using catastrophe theory. These properties are universal in catastrophe theory [36]:

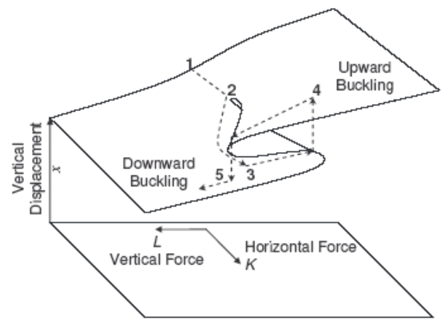

Figure 5: The cusp catastrophe surface for the beam-buckling example.

Sudden jumps - small changes in the control space can cause *catastrophic* changes in the state of the system.

Hysteresis - jumps to the left do not occur at same place as jumps to the right.

Divergence - two nearby trajectories can produce significantly different behaviour.

Bimodality - for some values in the control space, there may be multiple possible attractors. The actual state of the system will depend on its history.

Inaccessibility - for some values in the control space, there may be unstable attractors. A small change in the control space will shift the system away from this attractor.

4.1.3 Collaboration Example: Group Strategies

During collaboration, sudden discontinuous changes in behaviour are common. Collaborators shift suddenly from one strategy to another, discussion quickly shifts from agreeable to argumentative, and silent parallel work abruptly transitions to talkative coordination.

The parallel example in collaborative environments we consider is the interplay between group awareness, speed and

	Beam-buckling	**Group Awareness**
Sudden Jumps	Upward/downward buckling.	Switching between parallel and cooperative strategies.
Hysteresis	Different vertical force required to switch from up to down than from down to up.	When the importance of accuracy increases, the change in strategy occurs at a different place than when it decreases.
Divergence	Slight change in initial vertical force can dictate direction of buckling.	Slight change in initial importance of either speed or accuracy can dictate the strategy of a group.
Bimodality	For large K and $L = 0$, the beam can be buckled either up or down depending on the previous state of the system.	When both speed and accuracy are highly and equally important, the group can take on either a parallel or cooperative strategy.
Inaccessibility	For large enough K and $L = 0$, if the beam is flat, small perturbations in L will cause the beam to buckle.	When both speed and accuracy are highly and equally important, if the group is using a compromised strategy somewhere between parallel and cooperative, a slight change in either parameter will cause the group to adopt one or the other.

Table 1: Properties of catastrophe for beam buckling and group awareness.

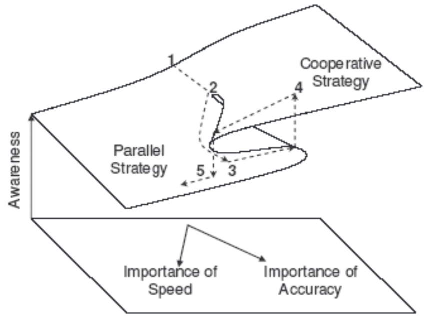

Figure 6: The cusp catastrophe surface for the group awareness example.

accuracy. We consider the variable of *group awareness* as our state space and the variables *importance of speed* and *importance of accuracy* as our control space. Table 1 draws a parallel between this example and the beam buckling example and demonstrates how to apply the above properties to identify catastrophe.

Because of these similarities, we model the interplay between these three variables with the cusp catastrophe and perform a similar manipulation of the control space (see Figure 6). The group members initially place no importance on either speed or accuracy and the group awareness is neither high nor low (1). The importance of both speed and accuracy increase simultaneously with no change in group awareness until a threshold value is reached at which point the group takes on a parallel strategy and the level of awareness drops suddenly (2). The importance of accuracy is then increased as the importance of speed is decreased (3). The awareness level of the group rises slowly until a threshold value is reached and the awareness level suddenly jumps up as the group takes on a cooperative strategy requiring significant coordination (4). An increase in the importance of speed and decrease in the importance of accuracy will similarly cause the awareness to drop back down as the group reorganizes into a parallel strategy (5).

Describing this situation using catastrophe theory is highly illustrative of the events that occur in collaboration. In particular, it is now clear why two seemingly similar groups can exhibit such dissimilar behaviour. This phenomenon has been observed in tabletop display studies [11]. Furthermore, this description provides a dynamic explanation of the events as opposed to a summary of the final outcome (e.g. mean and standard deviation).

The example taken from collaborative environments is not intended to be as mathematically precise as the physical example. Rather, it is intended to demonstrate the power of using the same mathematical tool to explain an observable phenomenon. The knowledge that this type of relationship can occur in a complex adaptive system allows the experimenter to gain a holistic understanding of how these variables may be interacting, despite the infeasibility of measurement. This explanation can then be used to help explain the underlying dynamics of the system as a whole.

4.2 Multiple Different Outcomes

Chaos theory is capable of describing more types of CASs than catastrophe theory, because it allows the analysis of strange attractors. This theory is based on the principle that complex *unpredictable* behaviour can emerge from simple deterministic rules. The property most characteristic of chaos is that a system's behaviour may appear random, despite the underlying determinism that dictates its behaviour.

4.2.1 Physics Example: Waterwheel

An example of a potentially chaotic system (adapted from [6]) is a waterwheel. In a waterwheel, water is poured into buckets which have holes that drain the water (see Figure 7). The motion of a waterwheel has a fixed-point attractor when the amount of water being poured into a single bucket is not enough to ever fill the bucket. The waterwheel has a limit cycle when the water is being poured at a medium pace and the buckets fill up enough to keep the wheel moving at a constant rate. The waterwheel also has a strange attractor when the rate of flow of the water is very high. In this case, the behaviour of the wheel appears erratic, speeding up, slowing down and changing direction, never settling into consistent predictable behaviour. Despite the complexity of this third case, the behaviour can actually be described using a system of mathematical equations and what is known as the Lorenz Attractor [29].

4.2.2 Properties of Chaos

Research in chaos has identified several methods that can be used to identify whether a CAS may be chaotic [4]. These

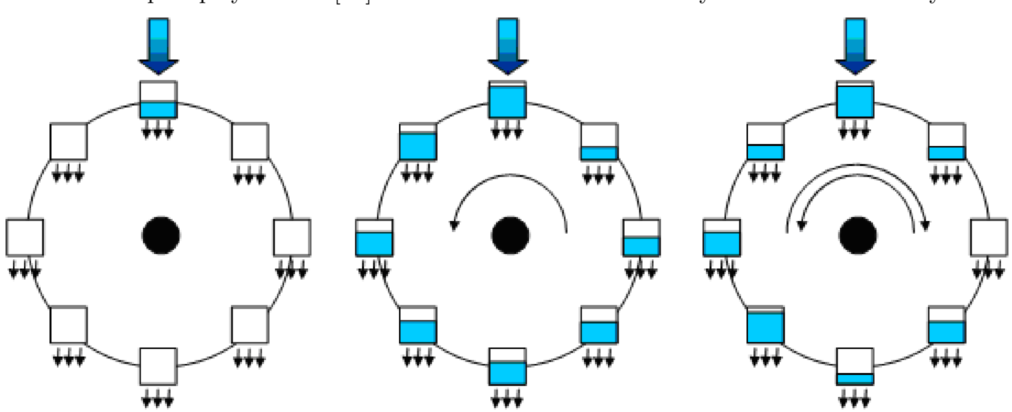

Figure 7: A waterwheel.

	Water Wheel	Changing Puzzle
Damped and Driven	The driving force of the waterwheel is the flow of water, which is continuous and the system is damped by the buckets losing water, which is also continuous.	The driving force of this system is the collective goal of the group to complete the puzzle and the dampening force is the regular perturbation of the puzzle.
Sensitivity to Initial Conditions	In the case of the waterwheel, a slight difference in the constant rate of flow of water can cause radically different behaviour to occur.	In the same way that two nearby points on a sheet of dough can become arbitrarily far apart when stretched and folded, two nearby puzzle pieces can be made arbitrarily far apart through the process of collaboration to solve the dynamically changing puzzle.
Bifurcations	The change in periodicity is observable in the waterwheel in its change in direction and speed of movement.	An initial strategy of edge completion may switch to filling in the centre and may then split again into completion of multiple patterns simultaneously. Another bifurcation may occur when some users share responsibility between completing an area and finding patterns.
Unpredictable Behaviour	Erratic behaviour of the waterwheel when water is flowing violently can be modelled by a set of partial differential equations. Though, due to the sensitivity of the system, slight measurement error can cause drastically different predictions than those that actually occur.	Despite the initial strategy that a group uses to solve the constantly changing puzzles, the eventual strategy will likely be an emergent and unpredictable phenomenon.

Table 2: Properties of chaos for a waterwheel and a changing puzzle.

include some mathematical approaches for detecting bifurcations [16] and sensitivity to initial conditions [34] and patterns in seemingly random data [4]. The properties of this and other chaotic systems are as follows [6]:

Damped and Driven - a chaotic system is simultaneously damped by an external force (or energy) and driven by an internal force (or energy). Chaos can result even when these forces are predictable, such as periodic or continuous forces.

Sensitivity to Initial Conditions - two similar initial states can tend to arbitrarily different results, and two arbitrarily different initial states can tend to similar results.

Bifurcations - chaotic systems exhibit sudden changes in periodicity. A repeated pattern of period two will suddenly branch into a repeated pattern of period four, and then eight and so on, until patterns of behaviour are no longer discernable.

Unpredictable behaviour - chaotic systems are characterized by their seemingly random behaviour. This behaviour, however, is not random, but simply appears that way to the observer.

4.2.3 Collaboration Example: Adaptive Planning

Collaborative environments exhibit some chaotic properties. To illustrate these properties, we consider the collaborative task of adaptive planning. For adaptive planning, while the end goal may remain constant, such as general health goals of a hospital, collaborators must continually adapt to the current state of the system in which such things as the number of patients and the state of their health is always changing. Other adaptive planning tasks include air traffic control, brainstorming sessions, fire fighting and other emergency response work. To simplify the explanation we model this as collaboratively solving a hypothetical jigsaw puzzle. Unlike a real jigsaw puzzle, this puzzle never gets completely solved. After a specific period of time (e.g. one minute), the puzzle is perturbed so that any “correct” pieces are no longer correct (e.g. by changing the picture on each piece). This ever changing puzzle models adaptive planning in that a move that was good a moment ago may no longer be appropriate. Similarities can be drawn between this hypothetical task and the example of the waterwheel. Table 2 draws this comparison.

Other dampening forces in collaboration might include time and space constraints as well as interruptions. The driving force will typically be a shared goal of the collaborators. Despite the periodicity of the perturbations and the perhaps predictable speed of motion of the collaborators, the actions or group strategies that follow may not be easy to predict.

Again, the example provided for collaboration is not as mathematically precise as the waterwheel example. Our intention is to demonstrate that chaos theory can help to understand the underlying behaviour of the complex adaptive system. An important consequence of realizing the presence of chaos in the underlying dynamics of collaboration is that collaboration cannot be easily predicted. We suggest that predicting behaviour in collaboration is similar to predicting the weather (yet another chaotic system). It may be possible to observe certain patterns (like seasonal changes), but a short-term forecast that describes the next state based only on the last, is a difficult (perhaps impossible) endeavour. This realization can help to guide the types of experimentation that researchers perform and can help to validate many of the observed results.

4.3 Computer-Supported Complexity

Despite the unpredictability and sudden changes that are ubiquitous in collaborative environments, it is possible to support this complex adaptive system with technology. In the above examples, the observed strategies of the group are what changes suddenly and may be unpredictable. A design lesson from this understanding is to support the seamless transition between these multiple strategies. For instance, the technology should not interfere with a group's decision to change at will (i.e. suddenly and unpredictably) from parallel work to coordinated collaborative interaction. The use of complex adaptive system theory may enable a move beyond the tradeoff between individual work and group awareness [9, 11] to a more holistic understanding of how to shift between the two.

In a recent study at an interactive tabletop [reference removed for blind review], we discovered that interface changes can make this transition more seamless. The interface adheres to the property of a CAS that agents within a CAS are only able to affect a change in their local environment. To cause a change at a distance, a local change must be invoked that in turn ripples through to the rest of the interface (using animation). These local changes eventually develop into the complexity which is fundamental to the system as a whole. Users of the system were observed to easily shift between individual work and coordinated activity. We also observed that users frequently took advantage of this ability to shift, in contrast to a previous experiment with an interface that did not adhere to this property [reference removed for blind review], where users typically would only shift strategies once or twice throughout the entire session.

In general, the recognition of the complexity and a more holistic understanding can help to inform the design of collaborative interfaces. Although CAS theory does not provide much in the way of a predictive model, this understanding will provide researchers with an intuition about what effect certain design decisions may have on a particular complex adaptive system.

5. CONCLUSION & FUTURE WORK

We have shown that collaboration can be described as a complex adaptive system. Describing collaboration in this manner expands our ability to analyze and evaluate this environment and therefore allows for a more informed design of supporting computer applications. In particular, CAS theory allows us to describe behaviour and activity beyond the bounds of linearity. This theory also provides a means for understanding collaboration as a dynamical (non-static) system that changes over time.

Because collaboration is a complex adaptive system, it is possible to observe chaos and catastrophe. The underlying theories that describe these systems can then be applied to the specific examples. These theories can be used as tools to provide a holistic understanding of the observed events.

Framing collaboration in this manner can help to inform what constitutes an appropriate study of this environment. We can borrow advice from the physical sciences and begin our studies with a generative strategy. This generative approach will help elucidate the most important aspects of what we now understand to be a complex adaptive system. We can then use this knowledge to "strip down" the environment to a minimal collaborative environment that maintains these key aspects. Study of this minimal (but still complex) system can then be used to understand the larger system.

Recognition that collaboration is a CAS also validates much of the current practice in evaluation of collaborative technologies. Despite not framing collaboration in this manner, many researchers have chosen an observational approach to studies and have recognized that analytical tools such as analysis of variance (ANOVA) and T-tests may not be suitable in this domain. As in other sciences that explore CASs, the analysis typically involves the search for complex patterns in the data, such as space usage [27], eye contact and physiological indications of fun and excitement [17].

In the future, we intend to apply CAS theory in the domain of CSCW in more detail. We will use the techniques and ideas outlined in this paper to explain a variety of phenomena that we have observed in our studies. Through this process, we intend to show that CAS theory will allow the exploration of previously unexplored and inherently non-linear aspects of collaboration.

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