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ABSTRACT

Noting that the chance to utilize a new paradigm is an opportunity that rarely presents itself, this paper suggests that chaos theory and communication can be combined to help understand human communication. The paper begins by examining the complexity of human communication--that is, the internal and external factors that affect the complexity of communication processes. The paper then assesses the reductive nature of both quantitative and qualitative research paradigms, suggesting that both paradigms inadequately address complex systems. The paper next discusses the properties of chaos theory, noting that it is part of a scientific movement to understand complexity and move away from reductionism. The paper summarizes the concepts of seemingly random behavior, sensitivity to initial conditions (referred to as the "butterfly effect"), mixing in finite time, and underlying order known as a "strange attractor." The paper next suggests that chaotic dynamics, and attributes of such, can be identified in research generated to support social penetration theory. The paper also describes a set of experiments conducted by Marshall Scott Poole that demonstrated the complex and perhaps chaotic nature of communication phenomena. The paper concludes that while there are potential imitations and difficulties in merging chaos and communication, there is also ample opportunity to hypothesize and test exactly where and how chaos can be combined with communication. Contains 58 references, a figure illustrating four types of attractors, and two figures of data. (RS)

An Argument for the Use of Chaos Theory

to Map the Complexity of Human Communication

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Abstract

This paper begins by examining the complexity of human communication. In particular, internal and external factors that affect the complexity of communication are reviewed. After examination of complexity, the reductive nature of both quantitative and qualitative research paradigms is assessed. In order to fully understand the complexity of human communication, a new research paradigm known as chaos theory, is offered. In particular the concepts of nonlinearity, strange attractors, and sensitivity to initial conditions, referred to as the "butterfly effect," are summarized. An initial search looking for evidence suggesting that some communication phenomena exhibit chaotic structures is conducted. In particular, research data generated to test theories of social penetration and decision making sequences are examined.

An Argument for the Use of Chaos Theory
to Map the Complexity of Human Communication

Chaotic dynamics has been evolving as a new paradigm for understanding phenomenon for several decades. The current direction of study in chaos promises a new view of phenomenon in communication, bringing with it dramatic testimony to the event we call human communication theory. Stewart (1993) regards chaos as:

A dramatic discovery whose implications have yet to make their full impact on our scientific thinking. The notions of predictions or of a repeatable experiment, take on new aspects when seen through the eyes of chaos. What we thought was simple becomes complicated, and disturbing new questions are raised regarding measurement, predictability, and verification or falsification of theories. (p. 2)

This paper is divided into eight sections, covering the following topics: (1) complexity of human communication, (2) isomorphism and content validity, (3) reductive nature of quantitative research, (4) reductive nature of qualitative research, (5) tenets of chaos, (6) social penetration data, (7) multiple sequence models of decision making, and (8) conclusions.

Because of the radical implications that chaos theory brings to any domain it touches, the chance to utilize a new paradigm is an opportunity that rarely presents itself. We feel that although it may present challenges in researching and teaching communication, our discipline requires us to see how chaos and communication can be combined to help understand human communication.

Human Communication as a Complex Process

"If nothing else, human communication is complex" (Fisher, 1978, p. 314). As Fisher states, human communication is a complex process. One way of understanding the complexity of human communication is to examine both the internal and external factors that influence communication processes.

<u>Internal Factors Affecting Complexity</u>

Individuals have a certain number of attributes that predispose them to the way in which information will be stored and used, called internal processes. Internal processes (also referred to as the cognitive system) are the methods by which individuals store, process, and retrieve information (Hewes and Planalp, 1987). These processes are extremely complex, and the forces guiding the development of individuals in unique ways are a result of organization within that individual. Hewes and Planalp (1987) divided an individual's internal processes into two main categories, cognitive processes and knowledge structures (p. 157).

Cognitive processes are described by Hewes and Planalp (1987) as how information is used and how the world is perceived, mainly through cognitive processes. Cognitive processes include focusing, inference, storage, retrieval, selection of plans, and implementation (p. 157). Further, each individual organizes and uses these features differently. Knowledge structures are how a person organizes information, and comprises the total of all the knowledge that a person has developed over their lifetime. In other words, communication is a highly individualistic, complex process. Fisher (1978) posits:

Under any circumstances, the effects of these retained portions of response remain within the individual and serve to modify the individual's behavior in later communicative events. Their effect may be long-range and, depending upon subsequent similar experiences, may effect observable responses at a later date. (p. 146)

The development of internal processes starts at the moment one can receive and categorize stimuli, and continues throughout life. Thus, we believe it impossible that different individuals bring to any given communicative event, precisely the same structures, information, or processing ability. Individuals cannot have exactly the same backgrounds because of unique internal processes and varied environmental influences. In summary, a variety of internal factors influence the process of communication making it extremely complex. In order to establish a more complete picture of the process of human communication, the external factors that add to the complexity of human communication need to be articulated.

External Factors Affecting Complexity

Reviewing all the external factors that influence the process of human communication is a task that exceeds the scope of this paper. Instead, this paper offers a brief review of a few of the external factors that affect complexity. In specific terms, the following factors are reviewed: (1) social identity, (2) group affiliation, (3) cultural background, and (4) language.

When two people talk, a complex interaction occurs because of differences in social identity. Masterson, Beebe, and Watson (1983, p. 8) suggest that an interaction between two people (e.g., you and a friend) should really be viewed as an interaction between the following six people:

1. Who you think you are
2. Who you think your friend is
3. Who you think your friend thinks you are
4. Who your friend thinks he or she is
5. Who your friend thinks you are

6. Who your friend thinks you think he or she is

This example demonstrates the complexity of communication in one type of interpersonal situation (e.g., friend to friend). If one were to examine all the social identities in a different context, such as a group of five people, the complexity might seem overwhelming.

Working from the interpersonal level to higher levels in the hierarchy of communication, a person's affiliation to groups will also influence the communication process. Goethals and Darley (1987) state we often join groups as a means of better understanding ourselves, our world, and others who cross our paths. Therefore, if groups influence our understanding of ourselves they will necessarily influence the way in which we communicate our understanding of ourselves to others. The influence of group membership on human communication is especially poignant when we realize that the average person is a member of eight groups at one time (Brilhart & Galanes, 1989).

In the broader picture, culture also has a substantial impact on the process of communication. One's culture can impose a system of attitudes, values, and beliefs on the individual (Porter & Samovar, 1991). A culture also influences one's view toward God, humanity, nature, and the Universe (Jain, 1991). Furthermore, culture can determine the level to which context determines meaning during interaction (Hall, 1991).

Finally, the use of language adds to the complexity of human communication. In fact, language is the most complicated of all forms of symbolism (Hayakawa, 1972). The complexity of language is so great that one must be "systematically aware of the powers and limitations of symbols, especially words, if they are to guard against being driven into complete bewilderment by the complexity of their semantic environment" (Hayakawa, 1972, p. 27).

The above examples show that a variety of both internal and external factors affect human communication, and therefore dramatically increase its complexity. As Fisher (1978) stated "If nothing else, human communication is complex" (p. 314).

Given the complexity of human communication, the communication researcher is presented with the following question: Should the process of human communication be reduced in order to easily understand it or should the complexity of communication be honored at the possible risk of clarity? One way to formulate an answer to this question is to review some key characteristics of valid measurement, such as isomorphism and content validity.

Isomorphism and Content Validity

Isomorphism of measurement refers to the notion that the complexity of a measurement model or instrument should parallel the complexity of the phenomena in question (Anderson, 1987). The concept of isomorphism of measurement stems from the mathematical definition of a "point by point relationship between two systems" (Reber, p. 377), in this case the measurement system and the social system. In other words, a measurement model must honor the complexity of what it is measuring; otherwise, the measurement model is distorting the phenomena in question. Most often, measurement models that are lacking isomorphism, are guilty of reducing or not encompassing the complexity of the phenomena. For example, cross sectional studies of human interaction are reductive because they compress the process of interaction to one moment in time.

Closely related to the concept of isomorphism, is the notion of content validity. In order to establish content validity the researcher must select a measure that specifies "the full content domain of the concept" (Frey, Botan, Friedman, & Kreps, 1992, p. 122). As previously discussed, human interaction is a highly complex process, involving many elements from numerous systems (e.g., social and information processing systems). Therefore, a measure must encompass the full domain of human interaction, including its complexity, to be content valid; however, it appears that current measures of human interaction do not honor the complexity of human interaction because the research paradigms (quantitative and qualitative) in which they are grounded are reductive. Below is a discussion of how both quantitative and qualitative research methods reduce the complexity of human interaction.

The reductive nature of quantitative research

Quantitative research methods are based on the theory of quantification, which states that any phenomena or object can be summarized by its parts (Anderson, 1987). Therefore, to understand an object or phenomena, all one has to do is to sum its parts. An example might help to illustrate the basic principle of quantification theory. A human being, such as George Bush, can be represented by identifying demographic characteristics, personality characteristics, and experiences throughout his life. Thus, George Bush can be reduced to a white male born in Milton, Massachusetts, who graduated from the Phillips Academy, joined the U.S. Navy and flew 58 combat missions in the Pacific, etc. (Rosenbaum, 1993, pp. 201-202).

One of the limitations of quantification theory, however, is that it does not allow for an interaction between parts. For example, the fact that George Bush graduated from the Phillips Academy has no influence on his experience as a pilot in World War II. In more general terms, this example shows that quantification theory does not examine how parts of an object are interrelated in a unique way. Instead, parts are separate and are assumed to be unrelated.

Quantitative methods also are reductive because they rely on statistics to analyze and interpret data. The very nature of statistics is reductive, as is true with most scientific analysis. As Babbie (1992) states "much scientific analysis involves the reduction of data from unmanageable details to manageable summaries" (p. 432). Babbie (1992) hints at an underlying tension between the level of detail in data and the level of conceptual clarity. That is to say, if researchers maintain a high level of detail when analyzing data, they will then threaten the clarity of the findings. For example, if a researcher collects 1000 points of data, explanation of all data points would be an overwhelming task and also would sacrifice clarity.

One way of increasing conceptual clarity, thereby reducing the level of detail, is to identify the point of central tendency (Blalock, 1976). When measured numerically, a variable is thought to cluster around a central point. The point of central tendency is thought to represent the essential characteristic of the variable, separate from any extraneous variables (Anderson, 1987). Statisticians operationalize the point of central tendency by calculating either a mean, median, or mode. The amount to which a point in the data set differs from the point of central tendency is labeled as unexplained variation or "error." Looking at a normal distribution, the apex of the distribution would be considered the point of central tendency. Any variation from the point of central tendency would be explained as measurement error. This is why the normal distribution was originally called the error law (Stewart, 1989).

To summarize the reductive nature of quantitative research take the following example (each number in a parenthesis indicates a reduction in complexity): A researcher identifies a phenomena, usually at one point in time (1). Next, the researcher selects specific attributes of the phenomena to be studied, usually a set of independent and dependent variables (2). The researcher then operationalizes the variables (3), meaning that observable manifestations of the variables are identified. A sample which represents the population of interest is collected (4). The variables are quantified by either observation (direct or indirect) or self-report (5). Summary measures are generated (6) and groups are compared and/or associations are made. Conclusions are based on whether or not the data array appears as patterned in an expected way (7) (explainable variance) or patterned in an unexpected or unpredictable way (unexplained variance, possible random fluctuations due to sampling error).

The above example illustrates seven possible ways in which the quantitative process is reductive. An expanded example of the quantitative research process would show that seven reductions is a very conservative estimate. In short, quantitative research is reductive by nature. The next section shows how qualitative research methods also reduce the complexity of human interaction.

The Reductive Nature of Qualitative Research

Qualitative researchers raise questions with the quantitative paradigm, because the approach oversimplifies system complexities and fails to examine major factors not easily quantified (Patton, 1991). Bostrom and Donohew (1990) further this notion, suggesting interpretivists see the basic assumption of empiricism as flawed (p. 111). They state "observation of an external world of events is impossible. If the world does not speak to us directly, but requires interpretation, then surely all knowledge is interpretive in nature" (p. 111). As agreeable as this notion may be, it does not honor, nor attempt to better explain, complex phenomena. The view that quality describes the complexity of phenomena beyond what quantity can is an unwarranted notion, in which "measurement is decried as yielding only a bare abstraction which falls far short of a qualitative description" (Kaplan, 1964, p. 208). For this reason, Kaplan (1964) states we are misconceiving qualitative and quantitative paradigms when considering one as "better" than the other. Both paradigms have their limitations, which is to say "no single quantitative description tells us everything; but is this not equally true of any single qualitative description?" (Kaplan, 1964, p. 207). Kaplan (1964) further suggests in regard to the difference between quantitative measurement and qualitative description:

> Having the experience does not consist in knowing anything whatever, at least in the sense of "knowing" relevant to the scientific context; it only provides an occasion for cognitions, and evidence of some sort (by no means conclusive) for their warrant. We are back to the argument that a measurement does not tell us everything; but neither does just one qualitative description (p. 209).

Kaplan is suggesting that qualitative description, although touted as an incomparable method of reaching an in depth understanding, is limited in usefulness. However, Patton (1990) argues qualitative methods strive for a system-wide understanding of phenomena beyond the use of description. He states:

> Interpretation, by definition, involves going beyond the descriptive data. Interpretation means attaching significance to what was found, offering explanations, building linkages, attaching meanings, imposing order, and dealing with rival explanations, disconfirming cases, and data irregularities as part of testing the viability of an interpretation. (p. 423)

What is significant in this qualitative view is that when reaching beyond the descriptive data, interpretation necessarily involves a large degree of reduction, thereby not capturing the complexity of human communication. For this reason, Patton (1990) cautions:

> It is the ongoing challenge, paradox, and dilemma of qualitative analysis that we must be constantly movin_ back and forth between the phenomenon of the program and our abstractions of that program, between the descriptions of what has occurred and our interpretations of those descriptions, between the complexity of reality and our simplifications of those complexities, between the circularities and interdependencies of human activity and our need for linear, ordered statements of cause-effect. (p. 424)

While qualitative analysis strives for holistic and in depth understanding, qualitative methods parallel the highly reductionistic themes in quantitative study through perceptual filters and data analysis.

The first way in which qualitative study reduces complex phenomena is through perceptual filters. Traditionally, the researcher is viewed as the instrument of both data collection and interpretation (Patton, 1990). Yet, when a human is used as an instrument, a necessary limitation is immediately introduced. Because the human condition involves limited scope of understanding, the human necessarily imposes reduction of phenomena. Unquestionably, a human being is incapable of simultaneously observing all phenomena, or universal interdependencies, occurring at any given moment. Stewart (1993) states our minds are simply unable to grasp the whole of the universe in fine detail (p. 216). Therefore, "be that as it may, our attempts to understand nature necessarily introduce scales of measurement that to us seem 'natural'" (p. 216). Fisher (1978) furthers this view of human as instrument. He states "the interpreter must identify, structure or organize, and discriminate among the stimuli received" (p. 148). Recognizing that a human observer, therefore, naturally engages in selective processing, Patton (1990) suggests "the data of the evaluation include whatever emerges as important to understanding the setting" (p. 42). Because relative importance may leave an unyielding gap in information, a paradoxical view of holistic understanding is created.

The second way in which qualitative study reduces complex phenomena is through data analysis. In an effort to organize the data collected through a qualitative investigation, categories of data are formed through coding and inductive analysis (Patton, 1990). This organizing of data is not only reductionistic, it often ignores the interaction between categories in a dynamic and complicated system. Patton (1990) suggests in qualitative study "the challenge is to make sense of massive amounts of data, reduce the volume of information, identify significant patterns, and construct a framework for communicating the essence of what the data reveal" (p. 372). This statement bares clear resemblance to Babbie's (1992) statement mentioned above with regard to statistics, "much scientific analysis involves the reduction of data from unmanageable details to manageable summaries" (p. 432).

An example of qualitative reductionism occurs within the data analysis method of Critical Incident. Query and Kreps (1993) suggest that the Critical Incident Technique (CIT) "is a straightforward, powerful, systematic, tightly controlled, yet adaptive, qualitative research strategy" (p. 64). Query and Kreps use a system initially developed by Flanagan (1954), which consists of three parts (each number indicates a reduction in the level of complexity). The three parts involve "identification of a general framework which will account for all incidents" [1]; "inductive development of major area and subarea categories that will be useful in sorting the incidents" [2]; "and selection of the most appropriate level of specificity for reporting the data" [3] (p. 65). The example again shows the remarkable similarity between quantitative and qualitative reduction of a complex system. Since both qualitative and quantitative paradigms inadequately address complex systems, further consideration should be given to a paradigm that leads to an understanding of a complex system that is purer in its holistic view.

Properties of Chaos

Recapping the previous pages, to date communication researchers have engaged in research techniques which are inherently reductionistic. However, a new paradigm, known as chaos theory, is part of a scientific movement to understand complexity and move away from reductionism (Waldrop, 1992). "The new discipline of chaotic dynamics is an analytical approach to the array of real-world dynamical systems that are random, irregular, aperiodic and unpredictable" (McDonald, 1992, p. 1476). Communication is a real-world dynamical system that has been researched from a comparatively <u>static</u> perspective by researchers. We believe a close inspection of chaos concepts may aid in researchers' future efforts to explain dynamical communication processes.

Defining chaos is admittedly a difficult task (Hobbs, 1993), because most scholars adopt "loose and unsatisfactory pictures of what chaos is supposed to be" (Batterman, 1993, p. 43). However, scholars concur that chaos theory serves as a way to identify the dynamics of a system by abstracting its underlying causal structure (Hobbs, 1993). Hobbs' (1993) statement, however, does not suggest that chaos theory serves as a framework for <u>all</u> types of systems, rather it is employed to analyze the <u>evolving structure</u> of systems that are classified as "chaotic." Therefore, to understand chaos theory, a definition of the concept, chaos, must be developed.

A satisfactory definition of chaos might be developed by identifying essential properties of chaotic systems, found in existing definitions of chaos, and then integrating these properties into a single definition. Toward attaining a clear integration, the following properties of chaotic systems are discussed: (1) seemingly random behavior, (2) sensitivity to initial conditions, (3) mixing in finite time, and (4) underlying order known as a strange attractor.

Seemingly Random Behavior

One of the most popular ways of identifying a chaotic system is to examine the likely behavioral outcome of chaos (Ford, 1989; Stone, 1989). A chaotic system produces seemingly random behavior. Chaotic systems are characterized as seemingly random because although they produce patternless or aperiodic behavior (Feigenbaum, 1983), their underlying structure is deterministic (Hunt, 1987). In a deterministic system, the state of the system is a "definite function of its state at the preceding moment" (Hunt, 1987, p.132). An example might clarify the coexistence of determinism and patternless behavior in chaotic systems. Consider the following equation, known as the logistic function:

(1.1) $x_{t+1}=kx_t(1-x_t)$ where $k=3.98$ and $x_0=.5$

The logistic function is deterministic in that x_1 can be perfectly predicted from x_0, x_2 can be perfectly predicted from x_1, etc. Therefore, relating back to the above discussion, equation 1.1 is deterministic because "the state of the system...is a definite function of its state at the preceding moment" (Hunt, 1987, p.132). However, when the logistic function (equation 1.1) is plotted on a time series graph the behavior of the system is aperiodic (Feigenbaum, 1983).

The logistic equation, frequently cited in chaos literature (Berliner, 1991; Eckmann & Ruelle, 1985; Feigenbaum, 1983; Gleick, 1987; Stewart, 1993; Wegman, 1988; Winnie, 1993), illustrates how a chaotic systems exhibits seemingly random behavior while at the same time possessing a deterministic structure. The discovery that a deterministic equation (i.e., the logistic function) produces aperiodic behavior has led to questions regarding widely accepted definitions of randomness (Wegman, 1988). Furthermore, some scholars suggest that the chasm between determinism and randomness has been bridged by chaos (Hunt, 1987; Wegman, 1988).

Sensitivity to Initial Conditions

The second characteristic of chaotic systems is known as sensitivity to initial conditions (Eckman & Ruelle, 1985), meaning that a small change in the initial position of a chaotic system produces exponential differences as the system moves through time. Sensitivity to initial conditions has been popularly referred to as the butterfly effect, which states that a butterfly flapping its wings in Brazil can set off a Tornado in Texas (Stewart, 1993).

Mixing in Finite Time

Chaotic systems are also characterized as mixing in finite time. Hobbs (1993) states that a system is mixing in finite time if "given any perturbation, no matter how small, there exists a finite amount of time after which the location of the unperturbed system is probablistically irrelevant to the location of the perturbed system" (p.124). Mixing in finite time can be illustrated with the logistic function. When graphed, the logistic function shows that a slight perturbation in the system, from x=.5 to x=.51 causes an exponential divergence in the two systems. In fact, the perturbed system (x=.51) appears to be unrelated to the unperturbed system (x=.5) by time 20.

One way of quantifying the phenomena of mixing in finite time is to analyze the amount of shared variance between the perturbed and unperturbed system as both systems evolve. The shared variance (r^2) between the perturbed and unperturbed system from time one to time ten is approximately .78 (or seventy-eight percent). However, from time eleven to time twenty the shared variance between the two systems is only .04 (or four percent). The radical difference in shared variance shows that by time twenty the perturbed system is probabilistically irrelevant to the unperturbed system.

Mixing in finite time, also known as exponential instability (Batterman, 1993), is a common characteristic of chaotic systems. In fact, Batterman (1993) argues that exponential instability is a necessary condition for a system to be classified as chaotic. Batterman (1993) does not argue, however, that exponential instability is a sufficient characteristic for classifying a system as chaotic.

Underlying Order

Although chaotic systems are characterized by aperiodic or seemingly random behavior, they possess an underlying order. Every chaotic system contains unique boundaries that give the system structure and order. The boundaries of a chaotic system constitute what is formally known as a strange attractor (Shuster, 1988). In an effort to explain the concept of a strange attractor, phase space (or the environment in which attractors emerge) must be examined. In addition, the general concept of an attractor should be examined in order to understand what differentiates an attractor from a strange attractor.

Phase space. Mathematics through numeric representation is explicit in the characterization of chaos. Yet, graphical depiction is equally important when examining chaotic behavior. Ruelle (1991) explains the relationship between mathematical understanding and graphical depiction:

> Mathematics is not just a collection of formulas and theorems; it also contains ideas. One of the most pervasive ideas in mathematics is that of geometrization. This means, basically, visualization of all kinds of things as points of a space" (Ruelle, 1991, p. 57).

As mentioned previously, chaos theory is used to describe the evolution, or temporal structure of a system. System evolution typically is examined using time-series graphs, that show changes in position over time.. In other words, time-series data is plotted conventionally as position versus time. However, conventional time-series graphs are not effective in illustrating chaotic behavior. Chaotic behavior is more easily and conveniently vi alized in phase space (Ditto and Pecora, 1993, p. 80). Phase space "refers to the domain in which the system operates. It provides an arena for the system's performance; it is the home of a system's attractor" (Priesmeyer, 1992, p.18). Phase space is based upon state space. That is, when plotted in state space, each data point represents an individual state, or potential initial condition, of the system. Phase space, then, is the evolution through all potential states (Tufillaro, Abbott, Reilly, 1991, p. 11). Phase space may be multi-dimensional.

Phase space is not a revolutionary concept. Many one-dimensional phase spaces were used at length in the early history of science (Abraham and Shaw, 1982, p. 7). For example, a graphic representation of one-dimensional phase space occurs when one places a thermometer under the tongue. The temperature moves from the state (temperature) which existed prior to application, toward a state reflecting the temperature of the body. As the temperature reaches 98.6 degrees, it levels to a continuous point. The path from the initial state to the final state can be charted in one-dimensional phase space providing a graphical representation of the thermometer's motion, or phase trajectory. Additionally, the value of 98.6 becomes visually obvious as a point of attraction. That is, if the initial state of the thermometer is higher than 98.6, the thermometer will reflect a drop in temperature to the steady state, and the opposite occurs as well. Additionally, the point 98.6 appears to "attract" the initial states toward itself, and therefore aptly is referred to as a focal point attractor (Baker and Gollub, 1992, p. 18).

Attractors. Formally defined, an attractor is a geometric form "in the phase space to which the phase trajectories of the dynamic system converge, or are attracted and on which they eventually settle down, quite independently of the initial conditions" (Ho-Kim, Kumar, and Lam, 1991, p. 191). In the one-dimensional example of the thermometer, regardless of the initial temperature, the result will eventually be a steady point value of 98.6. A steady state is not the case with the strange attractor; instead "the motion on a strange attractor has sensitive dependence on initial condition" (Ruelle, 1991, p. 64). In an effort to better illustrate the concept of both a point attractor and a strange attractor, let us now expand the number of dimensions of our phase space to two.

A two-dimensional representation of time-series data is a plot of the history of the temporal evolution of a variable, for example position and velocity of an object (Ditto and Pecora, 1993, p. 80). In a dissipative system (a system which loses energy), the graphical representation of the position and velocity of a traveling object would eventually converge to a fixed point representing a velocity of zero and a constant position (See figure 1). A thermometer in two-dimensions would exhibit this characteristic. Because of friction, many motions in nature form a point attractor. Even allowing perturbations, a system displaced from a steady state, eventually returns to its original steady and predictable state (Ho-Kim, Kumar, and Lam, 1991, p. 191).

The point attractor is one type of attractor, and the explanation of two other attractors will aid in the explanation of a strange attractor. A limit cycle (see figure 1) repeats the same motion over and over again (Stewart, 1993, p. 101). "It is a closed loop in the phase space to which the trajectories converge eventually" (Ho-Kim, Kumar, and Lam, 1991, p. 191). That is, trajectories converge into and continue with the cycle. Limit cycles differ from point attractors, in so much that one is unable to detect them by looking for a point of convergence, or steady state. "You have to look at a whole region. This is what makes periodic motion harder to detect than steady states. It's also what makes it much more interesting mathematically" (Stewart, 1993, p. 101).

The torus (see figure 1) is possible in three-dimensional phase space. With the torus, the trajectories again are not sensitive to initial conditions, and eventually settle down to the surface of the torus, "winding in small circuits around the axis of the torus while orbiting in large circles along the axis" (Ho-Kim, Kumar, and Lam, 1991, p. 191). To understand this quasi periodic motion:

> Imagine an astronaut in lunar orbit swinging a cat round his head in a space capsule...The cat goes periodically round the astronaut, the astronaut goes periodically round the Moon, the Moon goes round the Earth, the Earth round the Sun, and the Sun revolves round the center of the galaxy. That's five superimposed periodic motions...If you combine

two periodic motions whose periods have a common measure--that is, are both integer multiples of the same thing--then the result is actually periodic. If one motion has period 3 seconds, say, and the other 5 seconds, then the combination will repeat every 15 seconds.

But if there's no common measure--for example, if the periods are 1 second and $\sqrt{2}$ seconds--then the motion never repeats exactly. It does, however, 'almost repeat', in the sense that you can find states which are as close as you like to the initial state. This is why the name 'quasi periodic' is used. (Stewart, 1993, p. 104)

Because of the quasi periodic motion, the torus is often a good starting point for research into chaotic motion. However, the torus, as well as, the focal point, and the limit cycle, are all archetypes of "low dimensional attractors that characterize dissipative flows which are regular, that is stable and predictable to any degree of accuracy" (Ho-Kim, Kumar, and Lam, 1991, p. 191).

Strange attractor. Because the properties of seemingly random behavior, sensitivity to initial conditions, and mixing in finite time, are not present in the fixed point, periodic loop, and torus attractors, they have nothing "strange" about them (Ruelle, 1991, p. 64). In contrast, strange attractors (see figure 1) appearing in multi-dimensional phase space are indeed strange because of two fundamental properties. Ruelle (1991) explains that appearance and sensitive dependence on initial conditions distinguishes the strange attractor from other attractors:

First, strange attractors look strange: they are not smooth curves or surfaces but have "non-integer dimension"...next, and more importantly, the motion on a strange attractor has sensitive dependence on initial condition. (p. 64)

Let us examine the two aspects of strangeness more closely. Ruelle (1991, p. 64) first states that the strange attractor does indeed look strange. In contrast, the chaotic attractor has a phase space plot that is a complicated curve and never quite closes; however, after a time the attractor appears to sketch out a surface (Tufillaro, Abbott, & Reilly, 1991, p. 48). The chaotic attractor never intersects itself, because returning to a point already visited would create a motion that would repeat itself in a periodic loop (Gleick, 1987, p. 140). The irregularity of the motion of a strange attractor is the response to stretching and folding (Stewart, 1993, p. 143). Motion on an attractor stretches and folds. That is, motion will stretch to the bounds of the attractor, but eventually will have to fold back upon the attractor once the bounds are attained. "Although points close together move apart, some points far apart move close together" (Stewart, 1993, p. 143). The constant stretching and folding forces points to mix in finite time.

Ruelle (1991) refers secondly to the notion of initial conditions (p. 64). As noted previously, the method in which a chaotic system behaves is highly dependent on initial conditions. In other words, sensitivity to initial conditions suggests that each input "evolves into an overwhelming difference in output" (Morris, 1992, p. 331). The "butterfly effect" marks a chaotic system. That is, if "small perturbations remain small...instead of cascading upward through the system...the cycles would be predictable--and eventually uninteresting" (Gleick, 1987, p. 23).

Definition of Chaotic Systems

The previous discussion reviewed the four properties of behavior within a system classified as chaotic. Because previous definitions of chaotic systems are "loose and unsatisfactory" (Batterman, 1993, p.43), a definition of a chaotic system is offered below by integrating the properties of chaotic systems:

A chaotic system is a deterministic system that is mixing in finite time (exponentially unstable), including sensitivity to initial conditions, which produces aperiodic behavior that is seemingly random, yet contains an underlying order known as a strange attractor.

One additional note, a system should not be considered as purely chaotic or purely nonchaotic, instead chaotic systems may contain stochastic elements (Richards, 1992). Fortunately, methods have been developed for differentiating between chaotic behavior and stochastic behavior.

Altman and Taylor's Social Penetration Theory and Chaos

Chaotic dynamics, and attributes of such, can be identified in research generated to support social penetration theory. The social penetration process includes events that occur within growing relationships (Altman & Taylor, 1983, p. 3). One particularly strong theme exudes identifiable precepts of chaos. Altman and Taylor (1983) suggest that the process of social penetration is "orderly and proceeds through stages over time" (p. 6). This notion, when scrutinized, exhibits two dimensions of a chaotic system. First, unexplained variance and problems with replication of supporting research is attributed to unknowable initial conditions. Second, the characteristic of a strange attractor is identified.

Simmel (cited in Altman & Taylor, 1983), states "one can never know another person absolutely, which would involve knowledge of every single thought and movement" (p. 307). This refers directly to unknowable initial conditions, which had a pronounced effect on Altman and Taylor's (1983) work, as well as future researchers. In subsequent research to Altman & Taylor's (1983) initial work, Davis (1976) found it apparent "that the mean intimacy value of topics selected increased more or less linearly as the encounter progressed" (p. 789). While Davis (1976) states "the linear trend is very pronounced" (p. 789), it is readily apparent that numerous unexplained fluctuations exist. Figure 2 graphically depicts fluctuations which Davis (1976) ascribes the characteristic of progressing "more or less linearly" (p. 789). Further, in sharp contrast to a linear view Davis states "the rate of penetration was not uniform across dyads," and "when a total intimacy score was computed for each subject...variance between dyads was again significant" (p. 789). Although Davis (1976) began to address a complex system with a chaos paradigm, he failed to recognize the butterfly effect of unknowable initial conditions that can lead to such fluctuations in the data.

Altman and Taylor (1983), expanding their view of social penetration theory, believe that:

> The search for broad, single behaviors that apply to all dyads (e.g. more eye contact, more positive head nods, specific uses of space, etc.) is useful but will not be successful beyond a very general level. Rather we need to search out sets of complex behavior patterns and recognize that different dyads can develop unique patterns. (p. 131)

Stated differently, although there are somewhat predictable patterns in social penetration, there is no exact communication formula that works for all dyads. Only gross patterns, and generalizations exist. We propose that the general patterns of social penetration are in actuality chaotic patterns forming one or more strange attractors. The reason social penetration theory is not generalizable is in part because of the marked differences in initial conditions, but mostly that the system is so complex, it can not be described in a traditionally deterministic way.

The Multiple Sequence Model of Poole and Chaos

Marshall Scott Poole (1981) conducted a set of experiments that demonstrated the complex and perhaps chaotic nature of communication phenomena. In particular, he examined how task groups go about making decisions. He posited that decision making groups can go through one of many possible decision making sequences. Current thought to that point suggested that task groups followed a single decision sequence, such as:

(1) Orientation, evaluation, and control (Bales & Stodtbeck, 1951).

(2) Forming, norming, storming, and performing (Tuckman, 1965).

(3) Orientation, conflict, emergence, reinforcement (Fisher, 1970).

Each of these models suggested a linear decision making sequence. Only Scheidel and Crowell (1964) suggested that decision making was not linear. Instead, they suggested that decision making might be spiral in nature.

Poole (1981) also suggested that decision making is not a linear process. He posited that groups can go through numerous sequences and therefore a linear model of decision making does not adequately explain the decision process. Poole (1981, p. 1-24) advanced the following null and research hypotheses:

Null Hypothesis:

There is no between-group differences in developmental sequence. In other words, the relationship between time and communication behavior in a group is independent of group factors.

Research Hypothesis:

There will be between-group differences in developmental sequence. In other words, the relationship between time and communication behavior in a group is dependent on group factors.

To test his research hypothesis, Poole selected a set of ten groups. Four of the ten groups consisted of students selected a topic for a term project. The remaining six groups consisted of physicians performing a program planning task. Poole attempted to control initial conditions by checking for differences between groups on key variables, such as "FIRO-B, Machiavellianism, values, dogmatism, cognitive differentiation, and self-monitoring" (Poole, 1981, p. 6). Poole (1981) failed to find any significant differences between groups. Therefore, if groups were different, the differences were for the most part minor and unimportant.

The results of the experiment supported the research hypothesis, which stated that between-group differences would exist. In fact, the research hypothesis explained twice as much variance as the null hypothesis. Stated another way, the results indicated that even though groups were relatively similar, they structured their communication in very different ways. A chaos concept might easily explain this finding. Chaos theory states that slight changes in initial conditions can have a great effect on outcomes (a.k.a., the butterfly effect). In Poole's (1981) research, even minor differences in the groups would cause major differences in the way communication was structured.

Rather than explaining the complexity of the data, Poole (1981) instead reduced the complexity by summarizing trends, or in chaos terminology, looked for attractors. Poole (1983) described his method for reducing the complexity. He took the stream of interaction and imposed a coding structure, developed clusters, cluster-sets, phasic units, then phases. A look at the visual representation of the data (see Figure 3) would indicate, however, that the data is highly complex and reduction would significantly distort the interpretation of the data.

Conclusion

Most of the ideas in this paper are theoretical in the sense that our's is one of the first attempts at integrating chaos theory into communication. Because there are few others who have done this before, the relationship between chaos theory and communication can be considered to be in it's infancy. Precisely because it is young, communication researchers can gain an understanding of, and help contribute to, a new and potentially useful paradigm that is still in the process of being developed. However, this does not mean that chaos and communication should automatically be accepted.

Chaos theory has its roots in mathematics and science, where most of the chaos research is being conducted. Obviously, mathematics and communication do share many methodological techniques, but both disciplines are in many ways radically different. Therefore, while we see potential limitations and difficulties in merging chaos and communication, we also feel that there is ample opportunity to hypothesize and test exactly where and how chaos can be combined with communication. This is an excellent chance for all communication researchers to use the ideas presented herein to see if indeed a new paradigm can be found in the area of human communication.

Figure 1

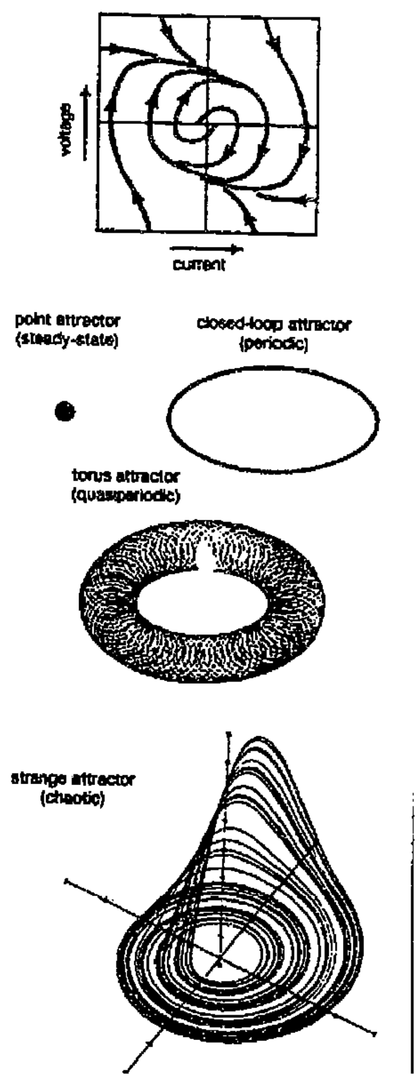

voltage
current
point attractor
(steady-state)
closed-loop attractor
(periodic)
torus attractor
(quasiperiodic)
strange attractor
(chaotic)

Figure 2

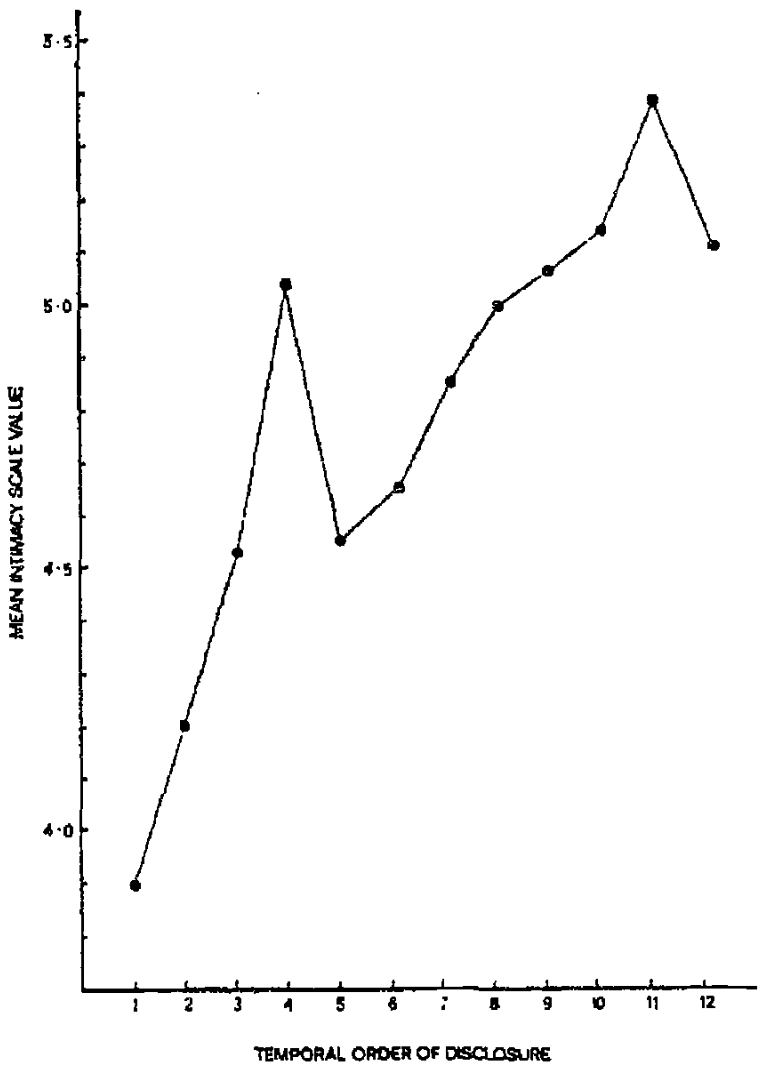
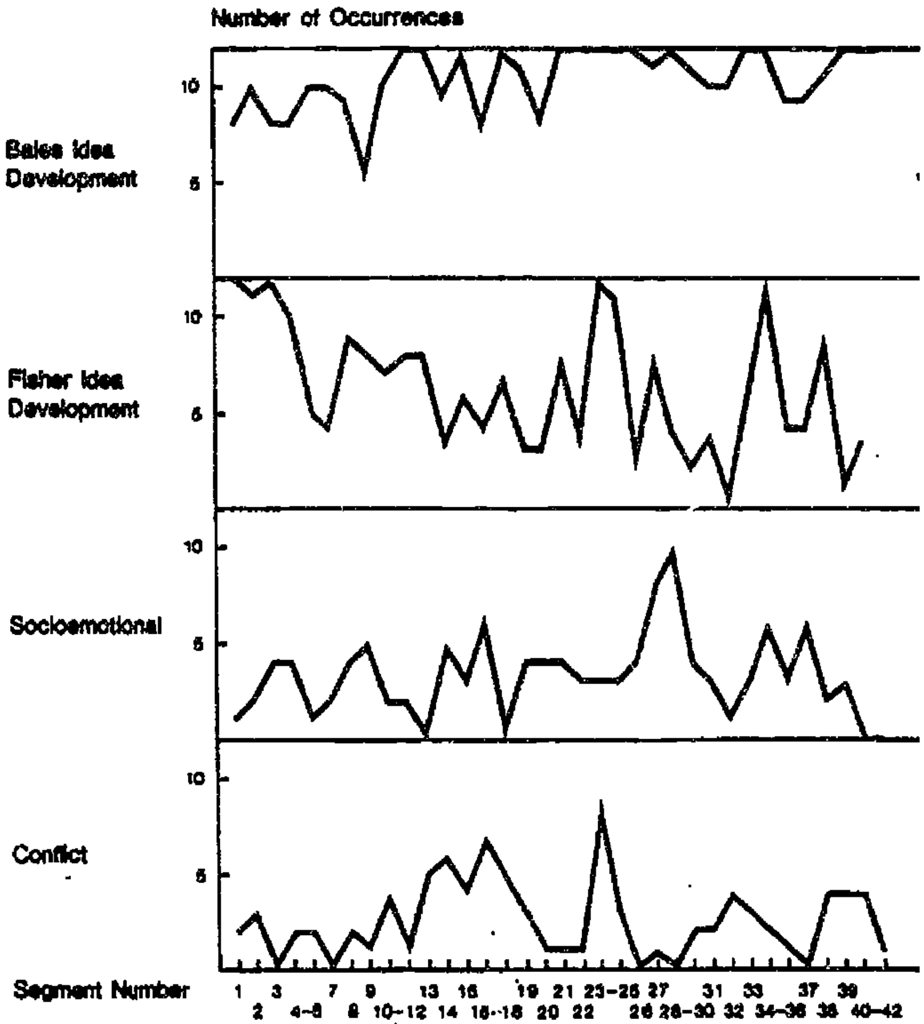

5·5
5·0
4·5
4·0
MEAN INTIMACY SCALE VALUE
1
2
3
4
5
6
7
8
9
10
11
12
TEMPORAL ORDER OF DISCLOSURE

Figure 3



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