Development and Psychopathology, **15** (2003), 641–669

Printed in the United States of America
DOI: 10.1017.S0954579403000324

Dynamic systems methods for models of developmental psychopathology

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Abstract
A survey of dynamic systems (DS) methods appropriate for testing systems-based models in developmental psychopathology is provided. The rationale for developing new methods for the field is reviewed first. In line with other scholars, we highlight the fundamental incompatibility between developmentalists' organismic, open systems models and the mechanistic research methods with which these models are tested. Key DS principles are explained and their commensurability with developmental psychopathologists' core theoretical concerns are discussed. Next, a survey of research designs and methodological techniques currently being used and refined by developmental DS researchers is provided. The strengths and limitations of each approach are discussed throughout this review. Finally, we elaborate on one specific dynamic systems method, *state space grids,* which addresses many of the limitations of previous DS techniques and may prove most useful for the discipline. This approach was developed as a middle road between DS methods that are mathematically heavy on the one hand and purely descriptive on the other. Examples of developmental and clinical studies that have applied state space grids are reviewed and suggestions for future analyses are made. We conclude with some implications for the application of this new methodology for studying change processes in clinical research.

Decades ago, Lewin (1931) criticized psychology for its overreliance on methodologies that were originally designed for studying closed, physical systems. These methods, he warned, were inappropriate for the study of complex, developmental processes. Over 70 years later, the same criticisms continue to be raised with increasing urgency. Specifically, leading theorists (Cicchetti & Cohen, 1995b; Ford & Lerner, 1992; Hinde, 1992; Kagan, 1992; Keating, 1990; Overton & Horowitz, 1991; Richters, 1997) suggest that there is a fundamental incompatibility between developmentalists' organismic, open systems models and the mechanistic research methods with which these models are tested. Developmental psychopathologists have been particularly concerned with their inherited mechanistic paradigm. Many of them have developed heuristically rich, complex models based on open systems concepts, but little headway has been made in finding alternative analytic tools appropriate for testing these models, a predicament Richters (1997) dubbed "the developmentalist's dilemma." Methods derived from dynamic systems (DS) theory may provide techniques critical for addressing this gap.

There are three objectives in the present paper: (a) to briefly outline key DS principles and highlight their commensurability with developmental psychopathologists' core conceptual concerns; (b) to provide a survey of research designs, methodological techniques, and measurement strategies currently being used and refined by developmental DS researchers; and (c) to elaborate on one specific DS method, state space grid (SSG) analysis. This approach (Lewis, Lamey, & Douglas,

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1999) was developed as a middle road between DS methods that are mathematically heavy on the one hand (and, thus, often inaccessible or inappropriate for the study of many phenomena in developmental psychopathology) and purely descriptive DS methods on the other. Our aim is not to present an exhaustive list of all the DS-based methodologies that have been developed. Rather, we have selected specific examples that seem to be most appropriate for addressing the types of research questions developmental psychopathologists tend to pursue. Our selection is also biased towards relatively simple techniques—there are some more sophisticated mathematical and graphical methods that are frankly impossible to describe with adequate detail in a review article. In the end, however, our main purpose is to provide a clear enough picture of various DS methods to inspire developmental psychopathologists to expand their analytic repertoire and, thus, move closer to testing their systems-based models.

The Developmentalist's Dilemma

Before proceeding to discuss DS theory and its methodological "bag of tricks," we will review briefly the strong rationale for developing new methods for the field of developmental psychopathology (also see Cicchetti & Cohen, 1995b). Developmental psychopathologists have adopted an organismic, holistic, transactional framework for conceptualizing individual differences in normal and atypical development (e.g., Cicchetti, 1993; Cicchetti & Cohen, 1995a, 1995b; Cummings, Davies, & Campbell, 2000; Garmezy & Rutter, 1983; Sameroff, 1983, 1995; Sroufe & Rutter, 1984). These scholars often frame their models in terms of organizational principles and systems language. The systems theories that inform these models include general systems theory (Sameroff, 1983, 1995; von Bertalanffy, 1968), developmental systems theory (Ford & Lerner, 1992), the ecological framework (Bronfenbrenner, 1979), contextualism (Dixon & Lerner, 1988), the transactional perspective (Dumas, LaFreniere, & Serketich, 1995), the organizational approach (Cicchetti & Schneider–Rosen, 1986), the holistic–interactionistic view (Bergman & Magnusson, 1997), and the epigenetic view (Gottlieb, 1991). As a class of models, these approaches focus on process-level accounts of human behavior and on the context dependence and heterogeneity of developmental phenomena. They are concerned with the equifinality and multifinality of development, the hierarchically embedded nature of intrapersonal (e.g., neurochemical activity, cognitive and emotional biases) and interpersonal systems (e.g., parent–child relationships; peer networks), and the mechanisms that underlie change (as well as stability) in normal and clinically significant trajectories.

As a result of inadequate measurement techniques, however, the complex developmental models informed by the language of systems thinking remain largely untested (Richters, 1997). For example, in the field of childhood aggression, a number of leading scholars have become concerned with highlighting the heterogeneity of aggressive youth and advocating the development of causal models that recognize the equifinality of aggression (e.g., Cicchetti & Richters, 1993; Hinshaw & Zupan, 1997; Moffitt, 1993). But it remains difficult to test these models because most of our current research methods and analytic techniques (e.g., regression analyses, *t* tests, path analyses) rely on strategies that aggregate overtly similar subjects into one group or another (e.g., aggressive and nonaggressive children) to conduct group-level statistical analyses. Thus, although we may know that aggressive children show the same behavioral pattern for very different reasons (e.g., abuse, permissive parenting, marital conflict, birth of a new sibling), this variability cannot be systematically addressed because multivariate analytic strategies carry an a priori assumption of within-group homogeneity. This is not just a niggling statistical detail. Several leading methodologists have argued that in most cases, these assumptions are completely unfounded and have likely led to serious misinterpretations of data (e.g., Hinshaw, 1999; Lykken, 1991; Meehl, 1978; Richters, 1997).

How did this gap between methods and developmental models come about? Numerous past critics (e.g., Hinde, 1992; Lykken, 1991; Meehl, 1978; Overton & Horowitz, 1991;

Richters, 1997) have pointed to psychology's "original sin" for an explanation: in an effort to gain credibility and align itself with the "hard" sciences, psychology appropriated the methods and analytic techniques of mechanistic, 19th-century physical sciences. This paradigm is inappropriate for the study of self-organizing, active, reactive, interactive, and adaptive organisms (i.e., the stuff of psychology). The irony is that psychology's embrace of this mechanistic paradigm came at the same time as the physical and biological sciences were advancing a radically new one, one based on open systems concepts (Overton & Horowitz, 1991; Richters, 1997).

For some domains of psychology, adopting techniques from statistical mechanics may not be as paralyzing, as it has become for developmental psychology (Thelen & Smith, 1994, 1998; Thelen & Ulrich, 1991; van Geert, 1998). At the heart of developmental questions, however, is how things *change*. By what process do novel structures (e.g., formal operational thought) or skills (e.g., walking, language) emerge? The pioneers of developmental science (i.e., Piaget, Vygotsky, Werner) concerned themselves with the pursuit of abstract laws or properties that govern development: the structural explanation of how development unfolds (van Geert, 1998b, 1998c). As van Geert (1998b) argued, however, change and the emergence of novelty may no longer be the focus of contemporary developmental psychology. This state of affairs can be traced to the "adoption of a statistics that was designed for different purposes, namely distinguishing populations characterized by some special feature . . . and estimating the linear association between the variance of some independent variable on the one hand and a dependent variable on the other" (van Geert, 1998b, p. 146). The adoption of such statistics seems to have missed the point of the original questions laid out by the founding scholars of developmental science (Thelen & Smith, 1994; van Geert, 1998b).

Developmental psychopathology, having grown in part from this tradition, inherited the same schism. It is interesting that developmental psychopathology also shares its roots with the founders of child psychoanalysis (e.g., Freud, Klein, Winnicott, Bowlby, Erikson) who, like Piaget and Vygotsky, formalized theories based on detailed observations of children in their natural environments (Cicchetti, 1990; Cicchetti & Cohen, 1995b). These original, individual-based, ethnographic methods, however, are rarely applied in contemporary research (but see Cicchetti & Aber, 1998; and Sullivan, 1998, for exceptions).

Thus, the field of developmental psychopathology seems to be at an impasse. On the one hand, some scholars have suggested that systems approaches to studying development have provided an interesting metaphor, but offer little more (Cox & Paley, 1997; Reis, Collins, & Bersheid, 2000; Vetere & Gale, 1987). Thus, one option is to give up the grail, abandon this well-intentioned enterprise, and build simpler, more appropriate models that can be tested with established statistical rigor. Another option is offered by Richters: "Resolving the developmentalist's dilemma will require more than a recognition of the inadequacies of the existing paradigm. It will require intensive efforts to develop indigenous research strategies, methods, and standards with fidelity to the complexity of developmental phenomena" (1997, p. 226). In the closing of his essay, Richters offered some general instructions for how this new generation of studies should proceed: (a) there should be intense focus placed on understanding *individuals* and the causal structures that underpin specific individuals' development, with particular attention paid to "well-characterized exemplars" (i.e., nonextreme) cases; (b) no single method should be held as superior or inferior (e.g., case based, variable based, cross-sectional, longitudinal, historical, ethnographic); instead, methodological pluralism should be encouraged and may vary in degree depending on the phenomena investigated; (c) "ritualized" hypothesis testing should be generally abandoned for more exploratory, creative approaches that emphasize the discovery process; and (d) a narrow focus on "explained variance" and prediction should take a secondary role to explanatory power. These directions provide the springboard from which to consider the potential contributions DS methods can make to addressing systems-inspired models.

Principles of DS

Developmental psychopathologists will be familiar with most of the concepts in DS theory because of their long-standing familiarity with systems concepts in general. Nevertheless, for the sake of clarity and precision, we believe it is important to delineate this framework from the ones mentioned previously. Formally, a DS is a set of equations that specify how a system changes over time. The principles that describe this set of equations make up a technical language originally developed in the fields of mathematics and physics. The terms that are most commonly associated with this framework include: attractors, repellors, perturbations, bifurcations, catastrophe, chaos, hysteresis, complexity, nonlinearity, far from equilibrium, and so on. Thus, what is referred to as DS theory in general is a *metatheoretical* framework that encompasses a set of abstract principles that have been applied in different disciplines (e.g., physics, chemistry, biology, psychology) and to various phenomena (e.g., lasers, ant colonies, brain dynamics) at vastly different scales of analysis (from cells to economic trends; Lewis & Granic, 2000).

Consistent with developmental DS theorists (e.g., Fogel, 1993; Lewis, 2000; Thelen & Smith, 1994, 1998), we use the term "DS" to refer to the systems themselves (not the equations) that change over time (Lewis & Granic, 2000). DS theory provides a framework for describing how novel forms emerge and stabilize through a system's own internal feedback processes (Prigogine & Stengers, 1984). This process is known as *self-organization* and refers to the spontaneously generated (i.e., emergent) order in complex, adaptive systems. In fields as various as physics (e.g., Haken, 1977), chemistry (e.g., Prigogine & Stengers, 1984), biology (e.g., Kauffman, 1993), and neuroscience (Freeman, 1995), DS principles have proven essential for providing process-level accounts of the structure and organization of system behavior, and changes in that structure over time (Lewis & Granic, 2000).

DS principles resonate with most systems concepts in general. DS approaches to development emphasize the multiple reciprocal interactions among system elements that are hierarchically nested and mutually influential. The context or ecology in which the system is embedded is critical for understanding a DS' behavior. Also consistent with various systems perspectives, development is conceptualized as movement toward greater levels of complexity through the interplay between positive and negative feedback cycles.

As will become clear from our selection of methods, we are most strongly influenced by the pioneering work of Esther Thelen, Linda Smith, Alan Fogel, Marc Lewis, and Paul van Geert, developmental psychologists who brought DS principles to the attention of the field at large. Because our focus is on methods specifically, a thorough discussion of DS concepts and their relevance to developmental science is precluded; thus, the reader is strongly encouraged to refer to reviews by Thelen and Smith (1994, 1998), Fogel (1993), and Lewis (2000). In the following discussion, we highlight some key principles and then move on to their methodological implications.

State space, attractors, and dynamic stability

Dynamic, self-organizing systems share several key properties, some of which have already been mentioned. One key feature of open systems is that, although theoretically they have the potential to exhibit an enormous number of behavioral patterns, they tend to stabilize in a limited range of these possibilities. Stable patterns emerge through feedback among many lower order (more basic) system elements; these patterns are referred to as *attractors* in DS terminology. Attractors may be understood as absorbing states that "pull" the system from other potential states. Behavior moves in a trajectory across the state space toward these attractors in real time. Over developmental time, attractors represent recurrent patterns that have stabilized and are increasingly predictable. As noted by Thelen and Smith (1994), all developmental acquisitions can be described as attractor patterns that emerge over weeks, months, or years.

As recurring stable forms, attractors are often represented topographically as valleys on a dynamic landscape. The deeper and wider the attractor, the more likely it is that behavior falls into it and remains there, and the more resistant it is to small changes in the environment. As the system develops, a unique *state space,* defined as a model of all possible states a system can attain, is configured by several attractors. Critically, living systems are characterized by *multistability* (Kelso, 1995); that is, their state space (i.e., behavioral repertoire) includes several coexisting attractors. Contextual constraints probabilistically guide behavior toward the dominant attractor at any given moment in time.

As we will see later, the concepts of state space, attractors and multistability have informed several research designs and methodologies in recent years. The operationalization of these principles, either graphically, mathematically, or heuristically, have helped DS researchers uncover previously undetected behavioral variability, as well as the processes by which this variability stabilizes into unpredicted, but nevertheless stable attractor patterns.

Interrelations between time scales

DS researchers are always fundamentally concerned with the interplay between different time scales. From a DS perspective, the same principles of change and stability can be applied at the moment to moment scale (real time) as they can to developmental time (weeks, months, years). The interplay between nested time scales is constant and reciprocal (Thelen & Smith, 1994, 1998). Self-organization at the real-time scale constrains self-organization at the developmental scale, which, in turn, constrains real-time behavior (Port & van Gelder, 1995). Thelen and Smith (1998) elaborate:

> . . . each behavioral act occurs *over time* . . . but every act changes the overall system and builds a history of acts over time . . . Habituation, memory, learning, adaptation, and development form one seamless web built on processes over time—activities in the real world. (p. 593)

Research designs based on DS principles almost always measure behavior on at least two time scales. The manner and extent to which the two or more levels of analysis are related to each other is subsequently examined. Thus, DS-informed studies often involve collecting real-time, observational data over repeated sessions in a longitudinal design such that moment to moment behavioral patterns and changes in those patterns can be traced along a longitudinal trajectory. The extent to which real- and developmental-time scales are interrelated is further clarified when considering perturbations and their relation to phase transitions.

Perturbations, phase transitions, and nonlinear change

Through the amplification properties of positive feedback, nonlinear changes in the organizational structure of a dynamic system can be observed. These abrupt changes are referred to as *phase transitions* and they occur at *points of bifurcation* or junctures in the system's development. At these thresholds, small fluctuations have the potential to disproportionately affect the status of other elements leading to the emergence of new forms. Novelty does not have to originate from outside the system; it can emerge spontaneously through feedback within the system. During a phase transition, these systems are extremely sensitive to *perturbations*. Between these points, however, self-organizing systems tend towards coherence and stability.

Phase transitions are characterized by interrelated changes in real and developmental time. In developmental time, periods of stability and relative predictability are followed by a phase transition characterized by disequilibrium and the destabilization of established patterns. After this period of flux, developmental systems restabilize and settle into new habits of interactions. Corresponding to this developmental profile, real-time behavior during a phase transition is more variable, flexible, and sensitive to perturbations; behavior may change from one state to another frequently and is less likely to settle in any one state for very long. However, before and after the phase transition, real-time behavior is far less variable: only a small number of behavioral states are available to the system; and once the system settles into one of these stable patterns, it tends to remain there for an extended time period (e.g., Thelen & Smith, 1994; van der Maas & Molenaar, 1992; van Geert, 1998a).

DS researchers have used the concept of perturbations on a real-time scale as an empirical design innovation to test the relative stability of observed behavioral patterns. Perturbations have the potential to abruptly "push" the system from one stable pattern to another (Fogel, 1993; Thelen & Smith, 1994). However, this is only a potential: whether and how a system becomes reorganized is determined by its underlying structure. Thus, context sensitivity for DS researchers is not just "a form of jargon for anything environmental, as if invoking the term suggests compliance with current scientific and conceptual canons" (Boyce et al., 1998, p. 145). DS researchers systematically observe changes in behavior, as it varies with contextual forces, in order to infer the underlying structure of the system (e.g., Fogel, 1993; Granic & Lamey, 2002; Lewis & Granic, 1999; Thelen & Smith, 1994; Thelen & Ulrich, 1991).

On a developmental scale, principles of nonlinear change, phase transitions, and perturbations have been most often used for the explicit purpose of studying the structural profile of developmental transitions (e.g., Fogel & Thelen, 1987; Lewis, 2000; Thelen & Ulrich, 1991; van Geert, 1991, 1994). Neo-Piagetian scholars such as van der Maas and Molenaar (1992) have used a particular type of dynamic model, the cusp-catastrophe model, to represent the nonlinear nature of stage transitions. Borrowing from Gilmore (1981), they suggest a number of criteria or "flags" that can be used to operationalize a transition. Among the transition flags are: a sudden jump from one parameter value to another, evidence of hysteresis (i.e., when the same conditions elicit different behaviors, depending on the immediate prior history of the system), anomalous variance, and increased sensitivity to perturbations. Transitions in motor, cognitive, linguistic and socioemotional development have been successfully modeled by the application of variants of these flags (Case et al., 1996; Lewis et al., 1999; van der Maas & Molenaar, 1992; van Geert, 1991, 1994). Structural changes in parent–adolescent interactions at the early adolescent stage transition have also been shown to exhibit the properties of a phase transition (Granic, Dishion, & Hollenstein, 2003; Granic, Hollenstein, Dishion, & Patterson, 2003). As we discuss in the final section of this article, change processes in psychotherapy can be examined empirically as phase transitions in individual development and may provide new insights about the appropriate developmental window for targeting interventions.

Many of the DS concepts described are clearly resonant with other systems views. But as a point of distinction, we suggest that there are four principles that are central to the DS framework which are either neglected or less emphasized in other approaches and which hold the most promise for new empirical directions. First, DS principles are primarily concerned with the emergence of novelty through the process of self-organization whereas, with some notable exceptions (Ford & Lerner, 1992), most of the emphasis in more general systems views is on mechanisms of stability (i.e., negative feedback processes, cybernetic models; Granic, 2000; Lewis & Granic, 1999). Second, although systems views may acknowledge the nonlinear nature of change in developmental systems, it is the hallmark principle in DS approaches to development and provides the foundation for a group of methodological strategies grouped under catastrophe theory (e.g., van der Maas & Molenaar, 1992) or the study of phase transitions. Third, variability represents critical data in DS research; it indexes a less stable, or multistable system, a system at a bifurcation point, and/or a system poised to change. Thus, measures of variability are often considered "the signal, not the noise" (e.g., Thelen & Ulrich, 1991). Fourth, DS theorists are fundamentally concerned with the interrelations between time scales of development and put a great deal of emphasis on understanding the unfolding patterns of real-time behavior (Thelen & Smith, 1998). This final principle is perhaps the most critical in terms of its methodological implications, and it is most often ignored in other systems frameworks.

In the following sections, we describe a number of dynamic systems approaches to research designs and measurement strategies. To limit the scope of our review, we will not be discussing connectionist or neural network approaches, nor will we touch on the exciting work emerging in the neurosciences (a field that has long embraced the principles of self-organization). We also spend much less time on the mathematical modeling techniques than the graphical, descriptive and statistical ones because we believe that the latter group of methodologies are generally more accessible and may ultimately prove more appropriate for the types of research questions put forward by developmental psychopathologists.

We first review some methodological and research design strategies put forth by leading DS scholars (e.g., Thelen & Smith, 1994; Thelen & Ulrich, 1991). Next, we discuss the types of data most suitable for DS analyses. We follow by providing a list of graphical techniques and quantitative strategies appropriate for the analysis of real-time and developmental data; these descriptions are supplemented with actual or hypothetical examples relevant to developmental psychopathologists. We also highlight the limitations inherent in some of the techniques and argue that a newly developed DS methodology, state space grid analysis, may help address a number of these weaknesses. The last part of this paper provides a detailed description of the state space grid technique which combines graphical methods with statistical analysis in such a way that fidelity to DS concepts is maintained. We provide several examples of programs of research and individual studies that have used variations of this approach.

Research Design Strategies Informed by DS Principles

Thelen and colleagues have explicitly laid out a methodological strategy for developmental psychologists interested in dynamic analyses (Thelen & Smith, 1994, 1998; Thelen & Ulrich, 1991). Their strategy includes six steps.

Step 1: Identify the collective variable of interest

A collective variable must be an observable phenomenon (not a construct or latent variable) that captures the coordination of the elements of a multidimensional system. Because Thelen and Ulrich (1991) were interested in motor development, they chose the phasing of alternating steps as the collective variable that condensed the many aspects of interlimb coordination. Changes in this collective variable can then be tracked over developmental time. This is the first step, and probably the most difficult to apply to developmental psychopathology; unlike in physical systems, it is exceedingly difficult to identify a collective variable in psychological systems. Extensive developmental observations and experiments are recommended as a first step towards this goal. An example relevant to developmental psychopathologists might be the observed intensity of a child's oppositional behavior, a collective variable that may capture the coordination of mood states, arousal level, appraisal processes, and so on (these processes themselves would need to be assessed in multiple contexts across different levels).

Step 2: Describe the attractors for that system

This involves mapping the real-time trajectory of the collective variable in various contexts across different developmental periods and identifying its relative stability. Thus, the contexts in which a child's oppositional behavior is most stable can be identified, as well as the contexts in which such behavior is less stable (i.e., more easily changed), is never observed, or is rarely observed. High stability indicates an attractor state. Attractor states may be tested by examining the variability of the collective variable given particular contexts (e.g., how often does the child become highly oppositional in response to a request to clean up at home vs. at school?).

Step 3: Map the individual developmental trajectories of the collective variable

This step requires collecting observations at many time points in a longitudinal design (also see Fogel, 1993). The density of time samples depends on the developmental period in question (i.e., in infancy, weekly observations may be needed, whereas in late childhood, data collected monthly might suffice; Fogel, 1993). Then, developmental profiles can be graphed on a case by case basis and the similarities and differences among profiles can be described. Stable (i.e., fixed or cycling) segments of the time series denote an attractor. At this stage, the multifinality and equifinality of developmental trajectories can be discovered. Some developmental profiles may start out looking similar and then, from very small differences that become amplified, trajectories may diverge. Other developmental profiles may show the opposite pattern of different initial conditions being "pulled" toward a particular attractor. The key at this stage is to create *individual* profiles rather than aggregate across subjects, otherwise, the variability inherent in developmental processes will be obscured. In developmental psychopathology, a similar point has been emphasized by researchers doing a case-based or person-oriented analysis (e.g., Bergman & Magnusson, 1997).

Step 4: Identify phase transitions in development

As described earlier, transitions in development are characterized by increased variability, a breakdown of stable patterns, and the emergence of new forms. The various catastrophe flags described earlier can help researchers identify points of transition. Transition periods are critical to mark because it is at this stage that researchers have access to, and may manipulate, mechanisms underlying change. This point is particularly relevant for developmental psychopathologists interested in clinical interventions. For instance, there may be normative stage transitions in children's development during which, as a result of normal maturational processes, the coordination among system elements begin to break down, previous attractors are destabilized, and there is potential for new patterns to emerge (e.g., Lewis & Granic, 1999; Lewis et al., 1999). Clinical interventions may have their greatest impact if they are targeted at these "sensitive periods." Also, interventions may *induce* a phase transition which may be one compelling way to characterize treatment progress. This possibility can be empirically verified by using simple descriptive statistics (e.g., looking for an increase in standard deviations and variance, and a break-down of correlations) or more formal techniques (described later in the section on SSGs). For example, treatment progress, operationalized as a destabilization of the system, may be tested by examining the observed amplitude of oppositional outbursts. Evidence for a clinically induced phase transition may include an increase in the standard deviations of the amplitude of outbursts and a decrease in *within-subject* correlations between, for instance, different contexts and the occurrence of oppositional behavior.

Step 5: Identify control parameters

In DS language, control parameters are the "agents of change." The purpose of tracking the collective variable across different contexts and developmental transition points is to ultimately identify the mechanisms underlying processes of change. Control parameters are not simply independent variables (although they can be considered a special type). Usually, independent variables are static measures which are assumed to have a linear effect on outcomes. Control parameters are continuous and changes in these values result in abrupt threshold effects on a collective variable. Moreover, these nonlinear changes occur at different values depending on whether the control parameter is increasing or decreasing. For example, through fine-grained longitudinal observations, Thelen and Ulrich (1991) were able to identify overall changes in muscle tone as the control parameter that was related to improvements in infants' treadmill stepping. In many areas of developmental psychopathology, however, this step is the most difficult because psychological systems are incredibly complex and the problem of identifying one or very few causal mechanisms that can be manipulated to test their impact on the system is often insoluble. Moreover, a control parameter may not always be something that *can* be manipulated (e.g., socioeconomic status, temperament, parental depression). Nevertheless, DS researchers urge us to at least keep the concept in mind for future studies, after careful microlevel observations have been completed.

Step 6: Manipulate control parameters to experimentally generate phase transitions

This suggestion is a familiar one to many developmental psychopathologists. Simply put, once a causal factor has been hypothesized from careful descriptive analysis, it should be experimentally manipulated to examine whether it does indeed trigger the expected shift in behavior. In this respect, intervention studies are an exceptional avenue for testing the role of specific control parameters in developmental psychopathology (e.g., Dishion, Bullock, & Granic, 2003; Dishion & Patterson, 1999; Eddy & Chamberlain, 2000; Forgatch & DeGarmo, 1999). One of the best examples of following this proposed strategy comes from the work on the etiology and treatment of aggressive behavior. For instance, based on decades of microsocial observational studies with families, coercive parent–child interactions have been identified as a causal mechanism underlying the etiology of childhood aggression (e.g., Patterson, 1982; Patterson, Reid, & Dishion, 1992). To confirm these findings experimentally, Forgatch and DeGarmo (1999) investigated the impact of a randomized control intervention that aimed to decrease the rate at which parents engaged in coercive interchanges. Results confirmed that, indeed, changes in parenting resulted in decreases in children's aggressive behavior. From a DS perspective, parental attitudes toward discipline, for example, could have been the control parameter that was adjusted through the intervention. Again, it is important to note that many developmental psychopathologists already manipulate control parameters. The unique contribution of Thelen and Smith's work is contextualizing this step within the broader framework of DS theory, which provides specific rules about the types of control parameters to manipulate and the nature of changes in the collective variable (Thelen & Smith, 1998).

Despite the advantages of Thelen and Smith's (1998) approach, there are some problems with implementing their general strategy. First, it requires collecting continuous time-series data (e.g., physiological data, behavioral observations coded in real time); this type of data is time consuming and expensive to collect. More importantly, time-series data may not capture the type of information pertinent to many developmental psychopathologists. Second, and related, unlike motor or cognitive development in which some skill or task performance increases or decreases quantitatively over time, psychopathology may not involve such graded changes (cf. Lewis et al., 1999). Instead, the development of psychopathology may better be characterized as emergent patterns of interconnected changes in different domains (e.g., biological, cognitive, emotional) that are nonlinearly related to one another and change qualitatively, as well as quantitatively. We will address this issue at greater length when we discuss SSG analysis and the limitations it addresses in this regard.

Suitable Data for DS Analyses

There are several types of data that developmental psychopathologists collect that are appropriate for DS analyses. Because a DS perspective is fundamentally about changes in time, the most important data characteristic is that there are multiple measurements over time. Thus, questionnaire data collected at one, or just a few, time points would be inappropriate for tapping processes that unfold over time (cf. Cummings et al., 2000). Below we list the four types of data that lend themselves most easily to DS analyses and name some examples of analytical techniques that can be conducted. These techniques are then explained in more detail in the following section. Table 1 lists the techniques and the appropriate data types for each and provides examples of empirical papers that have applied the various DS methods.

Type 1: Observational data—continuous

These data are obtained in time units of less than 1 s; these data often comprise physiological measures. The density of data points allows for the more sophisticated techniques

Table 1. *Summary of DS methods and related data types, DS concepts, and studies applying these techniques*

Techniques	Type of Data: Obs-d	Obs-c	Dev-s	Dev-l	DS Concept	Examples
Graphical						
Phase plots	*X*	*X*	*y*	*y*	Phase space Attractors	Bakeman & Gottman (1997) Granic & Dishion (2001) Sabelli et al. (1995) Totterdell et al. (1996)
Karnaugh maps	*X*	*y*	*y*	*y*	Phase transition State space	Dumas et al. (2001)
SSGs	*X*	*y*	*y*	*X*	State space Perturbation Attractors	Granic & Lamey (2003)
Real time						
Case studies			*X*	*X*	Self-organization	Fogel (1990, 1993)
Fourier analysis	*X*	*y*			Attractors	Newtson (1994, 1998) Schroeck (1994)
Coupled equations	*X*	*X*			Feedback	Gottman et al. (1997) Nowak & Vallacher (1998) Ryan et al. (2000)
Nonlinear dynamics	*X*	*X*	*X*	*X*	Attractors Phase space Feedback Chaos Determinism	Guastello (2001) Heath (2000) Newell & Molenaar (1998)
SSGs	*X*	*X*			State space Attractors Phase transitions	Lewis et al. (1999)
Developmental						
Descriptive developmental profile			*X*	*X*	Phase space Attractors Self-organization	Thelen & Ulrich (1991) Thelen & Smith (1994)
Dynamic growth modeling			*X*	*X*	Phase space Attractors Self-organization	van Geert (1994, 1998) Ruhland & van Geert (1998) Thelen et al. (2001)
Catastrophe			*X*	*X*	Phase transition Hysteresis	Hartleman et al. (1998) van der Maas & Molenaar (1992)
SSGs			*y*	*X*	Phase transition State space	Granic, Dishion, et al. (2003) Granic, Hollenstein, et al. (2003)

Note: Obs-d, observation discrete; Obs-c, observation, continuous; Dev-s, developmental short; Dev-l, developmental long. *X*, data that were actually used in the study; *y*, data that could potentially be used with the method.

adopted from the natural sciences where this type of data is most common. These techniques are often based on time-series analysis and include the domain of elaborate mathematical models based on coupled equations and catastrophe models. Quantitative measures of chaos—Lyupanov exponents, entropy, correlational dimensions, and so on—can also be derived from such continuous data. Furthermore, all of the methods available to the other data types are available with this kind of data as either time series or summaries of time series.

Type 2: Observational data—discrete

This includes live and taped observational data that are converted to codes along time units as small as 1 s. These codes can represent the sequence of behavior for one or more subjects and are typically inappropriate for time-series techniques unless they have sufficiently dense data points. For the purposes of this paper we will also include in this category observed measures of one point in time, as these data can be used with a small subset of the methods described below. By applying DS graphical techniques such as state space grids, Karnaugh maps, and phase plots, the temporal patterns embedded in the temporal sequence can be uncovered. These data can be used to identify attractors, perturbations, phase transitions and other DS patterns.

Type 3: Longitudinal data—short

This type of data may be thought of as a special case of discrete time-series described in data type 2. It can include, for example, hourly/daily/weekly self-report measures (e.g. diary or "beeper" studies), repeated phone interviews, or repeated observational sessions (e.g. therapy sessions). The time points may be frequent enough to allow the use of some of the real-time techniques available to the second type of data or may be analyzed using techniques applicable to developmental-time data (Type 4).

Type 4: Longitudinal data—long

The last type includes any combination of the above data types collected at different time points that may span weeks, months, or years. The main distinction from data type 3 is the time span between the first and last measurements. Data collected in three or more waves is often used to depict change, growth, or intervention effects; and a variety of DS methods including SSG analysis, dynamic growth modeling, developmental profile analysis, and catastrophe modeling can be applied. Developmental phase transitions are detectable through the application of these techniques.

Real-Time Measures

As most teachers of research methods and statistics in general will insist, "eyeballing" your data is an important part of the analytic procedure. For DS researchers, graphical techniques provide the core of their analytic armament. Perhaps because dynamic systems theory is a descriptive framework and because it aims to describe phenomena in geometric terms (recall our discussion of behavioral trajectories on a state space), plotting data is the mainstay of DS researchers (Abraham, Abraham, & Shaw, 1990; Norton, 1995). As described below, a number of these real- and developmental-time graphical methods can be complemented with various quantitative tools.

Case studies

Perhaps the one common recommendation DS researchers offer is to start with fine-grained, real-time observations of the phenomenon of interest and follow this behavior across a significant developmental period. One of most basic first steps toward this end is the careful description of case studies. Fogel's (e.g., 1990, 1993) research on mother–infant relationship processes is exemplary in this respect. His research relies heavily on detailed descriptions of videotaped interactions, as they proceed in real-time. He uses these case histories as a "means to seek patterns in sequences of action in a context, in both real and developmental time scales" (Fogel, 1990, p. 343). Metaphors based on DS principles serve as guides for identifying dynamically stable dyadic patterns and changes in those patterns across development. Although these narrative descriptions are rich in detail and provide ample fodder for generating hypotheses, they are intentionally not quantified. As such, this method does not address developmental psychopathologists' search for techniques to test their conceptual models.

Phase plots and time series

Phase portraits most generally are state spaces filled with behavioral trajectories. More often these plots are called phase plots when the variables being plotted are dynamic, such as velocity and displacement. With the continuous data sometimes used by developmental psychopathologists, it is possible, for example, to create plots that depict the magnitude of change against the rate of that change (e.g., with galvanic skin response or heart rate data).

For the more common type of discrete observational data that developmental psychopathologists collect, phase space can be "reconstructed" by plotting behavior at time T against behavior at time $T + 1$ (sometimes called a lag 1 plot). These types of plots can alert researchers to different types of attractor states (i.e., cyclical, fixed point, oscillating) and, thus, uncover process-level information not otherwise accessible. For example, in a recent study, Granic and Dishion (2001) used phase plots to explore the dynamic patterns underlying adolescent friendship interactions. Past research suggested that antisocial adolescents can be distinguished from their prosocial counterparts by the extent to which they engage in reciprocal deviant talk (e.g., talk about stealing, lying; Dishion, Capaldi, et al., 1995; Dishion et al., 1996, 1997). Observational studies showed that antisocial peers had a higher mean duration of deviant talk than prosocial peers. Central tendency measures, however, do not speak directly to the processes underlying these interactions. Moreover, they obscure potentially critical temporal patterns. To come closer to a process-level explanation, we began by conceptualizing deviant talk as an attractor for antisocial, but not prosocial, peers. Thus, our interest was not in examining whether one group showed more deviant talk than another, but whether, over the course of an interaction, antisocial adolescents became increasingly engrossed in topics organized around deviancy. One way to explore this hypothesis was to examine whether, as the interaction unfolded and antisocial dyads repeatedly returned to talking about deviant topics, they also spent increasingly more time in that deviant pattern. Phase plots were created as a first step toward examining this question.

"Deviant" (or "rule-break") and "normative" talk were coded continuously from videotaped interactions between best friends. A time series representing the duration of each successive bout of deviant talk was created for each dyad. Then, using a "floating window," we plotted each value on the time series such that the duration value at time t was represented on the x axis and the duration value at time $t + 1$ was plotted on the y axis. The plots look much like scatterplots of first-order autocorrelations except that a trajectory connects successive points; thus, the temporal integrity of the interaction is maintained. Figure 1 is an example of an antisocial dyad's phase plot. The plot shows that this dyad began with very short durations in the deviant (rule-break bout on plot) talk pattern (points 1–3), but, over time, they spent more and more time in this state (points 49–52). The plot suggests that for this antisocial dyad, antisocial talk was an attractor state, the strength of which held the dyad in the pattern for longer and longer time periods. Eventually, this dyadic system may move toward continuous deviant talk. There are several other possible patterns that phase plots can exhibit. For example, a large proportion of prosocial dyads showed a relatively "random" phase plot similar to the example presented in Figure 2, suggesting that deviant talk was not an attractor for these peers.

Bakeman and Gottman (1997) analyzed data from marital couples' interactions using this technique, except they plotted the inter-event interval between successive displays of negative affect (i.e., the time in between one negative affect and the next, across the interaction). They showed that, for distressed dyads, the time between each negative affect display became shorter and shorter over the course of the conversation; thus, negative affect was an absorbing state for distressed couples.

Fourier analysis or spectral decomposition

This technique can be used for finding periodicities (i.e., cyclic patterns) in time-series data

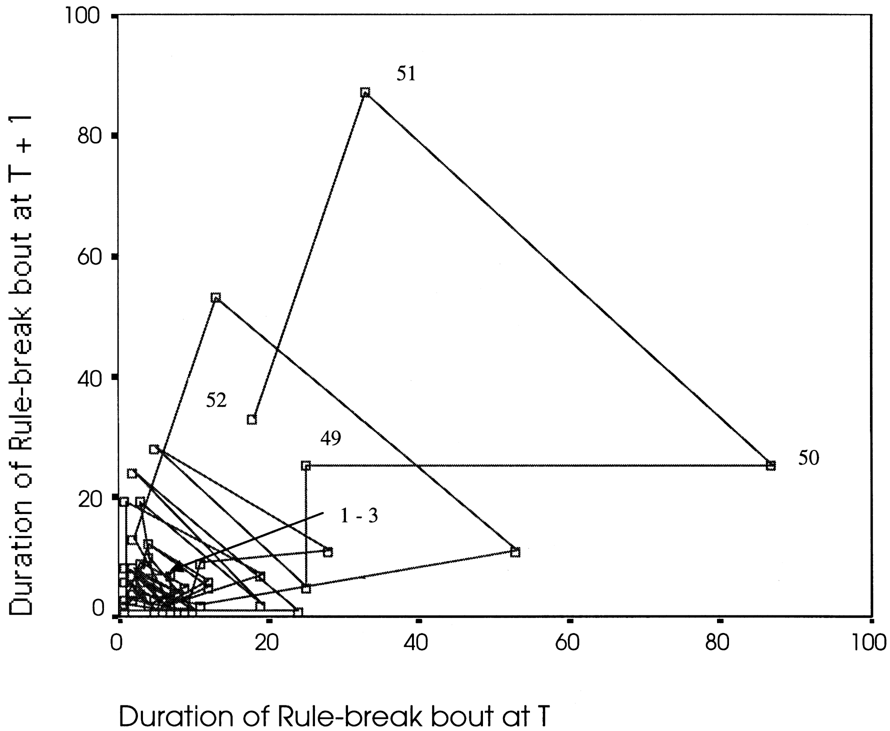

Figure 1. A phase plot for an antisocial dyad.

such as those used in phase plots. In general, this procedure treats a time series as a wave form, breaks it down into a collection of pure waves of uniform frequency, and identifies the most prominent waves (Schroeck, 1994). Newtson (1994, 1998) used this method to analyze the coupled dynamics of dyadic interactions. The relative amplitudes and temporal synchrony of these "behavior waves" were associated with the degree of mutuality or competition in interpersonal relationships. In other applications, different types of attractors including oscillating and periodic attractors can be identified. For behavioral scientists, however, this method has its limitations. Like all time-series procedures, it requires the researcher to collapse meaningful categorically coded observational data into one or very few continuous dimensions (e.g., Bakeman & Gottman, 1997). For example, most observational coding schemes used in developmental psychopathology (e.g., SPAFF, Gottman, McCoy, Coan, & Collier, 1986; FPC, Dishion, Gardner, Patterson, Reid, & Thibodeaux, 1983; MAX, Izard, 1979) code discrete behaviors like "contempt," "argue," "beligerance," and "whining." To conduct Fourier analysis, these codes would have to fall along a single dimension (e.g., intensity of negativity). This type of collapsing is often either conceptually unfeasible or unappealing because of its oversimplification.

Karnaugh maps

Inspired by synergetics, a type of dynamics developed by Haken (1977), Dumas, Lemay, and Dauwalder (2001) adapted this technique from Boolean algebra to study parent–child interactions. Karnaugh maps depict all possible combinations of up to four binary variables in one table or grid. A simple two-variable Karnaugh map is basically a cross-tabulation of event frequencies with one dichotomous variable to each axis. Three- and four-variable maps are somewhat more complicated. Figure 3 shows a schematic four-variable Karnaugh map. Each variable (*A, B, C,* and *D*) can have a value of 0 or 1 and each is displayed on one side of the square table (bottom, left, top, and

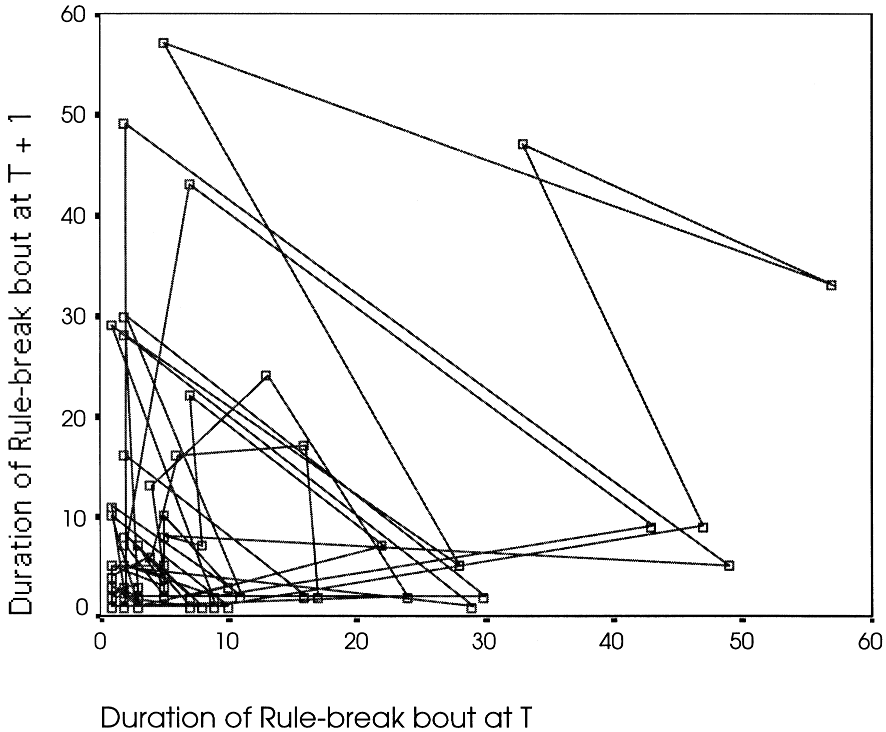

Figure 2. A phase plot for a prosocial dyad.

right). Each cell in the map can be represented as a unique combination of the binary values of the four variables. Thus, a Karnaugh map is a state space of all possible states of the system and represents the relative frequencies in each state. Dumas and colleagues (2001) extended the application of these maps by plotting the transitions between states to depict temporal patterns across the space.

In their study, Dumas et al. (2001) plotted every minute of 6-hr home observations according to four parent and child dichotomous variables that included control, compliance, aversive behavior, and positive behavior. Each behavior was plotted according to the four-variable configuration, and successive behaviors were connected by a trajectory. The researchers were primarily interested in comparing the maps of clinically referred dyads with randomly selected controls. They analyzed the "recurring transactions" (i.e., attractors) that were found most frequently in each group and aggregated these findings graphically on one summary Karnaugh map. Their results showed differences in transactional patterns between the groups, mostly involving positive interactions and cycles of maternal control and child compliance. In addition to the graphical depiction of interaction sequences, the authors computed a "complexity index" that was designed to quantify each map on a continuum from completely deterministic to completely random. They found that all maps, regardless of group assignment, were neither random nor deterministic. While this approach was unique and interesting (particularly from a methodological standpoint), from a DS perspective there is no reason to think that social behavior, especially in dyads with a rich history, is ever random or ever completely determined. Nevertheless, the complexity measure has a great deal of potential. For example, it might be used to determine whether stable coercive parent-child interaction patterns become less determined (i.e., the old attractor patterns break down) over the course of a treatment program.

Karnaugh maps hold a great deal of promise for several reasons. First, because this method allows for the representation of be-

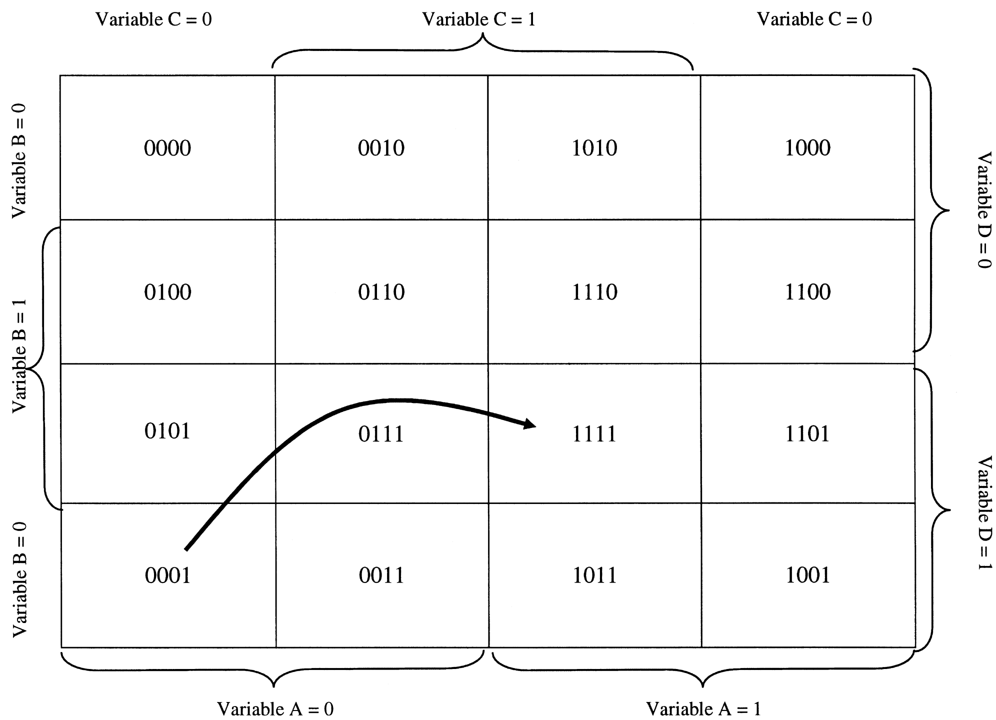

Figure 3. The schematic of a four-variable Karnaugh map. Each cell is a unique combination of four binary variables. The arrow shows a sample transition from one state, where only variable *D* is present (i.e., only *D* = 1), to the next state in time, where all four variables are present (i.e., all = 1).

havior in up to four dimensions (five if you count time), a great deal of the complexity in interactional behavior can be nicely captured. The temporal quality of dyadic behavior is also maintained and can be tracked easily through visual inspection. Moreover, the systemic properties of dyadic interactions are kept intact, instead of having to fall back on conventional methods that often require analyzing each dyad member separately.

However, this methodology as applied to behavioral science is very much in its infancy; thus, there are some limitations that may need to be addressed before Karnaugh maps can be applied to a broad range of behavioral data. One problem is that the adaptation of these maps to behavioral research requires data that can be collected or converted into dichotomous variables that occur concurrently. Developmental psychopathologists are often interested in data that cannot be meaningfully transformed into dichotomous values; continuous or categorical data cannot be adequately captured with these maps. Also, this method does not provide quantifiable tests of the strength of the patterns within dyads, or between patterns within or across groups. In this respect, the new developments in SSG analysis may provide some promising avenues. Although the two approaches are not entirely similar, the quantitative measures that may be derived from SSGs may also be applicable to Karnaugh maps.

Coupled equations

Most generally, this method refers to the use of paired equations derived from two synchronized time series that produce parameters describing the underlying dynamics of a system. The use of coupled equations may involve mathematically intense procedures and often requires fine-grained time-series data or simulated data; hence, these methods are often not applicable to the data types used by developmental psychopathologists. However, one successful application in the field has been the work by Gottman and colleagues, who have used coupled differential equations to model the dynamics of marital couples and to predict, from those dynamics, couples who will remain married or will divorce (Gottman, Coan, Carrere, & Swanson, 1998; Ryan, Gottman, Murray, Carrere, & Swanson, 2000). They have also used this method to study how peer interactions influence the behavior of developmentally delayed versus normal children (Gottman, Guralnick, Wilson, Swanson, & Murray, 1997).

Gottman's technique uses a time-series of coded observational data (either marital interactions or peer interactions) to create an equation for each dyad member. According to this model, one person's behavior at time t is a function of his or her behavior at time $t - 1$ plus the other participant's behavior at time $t - 1$, plus an "influence function." These equations are iterated across the length of the time series, and the results for each equation are graphed separately on one plot. The values at which each members' trajectory intersects with the other are considered attractors for a particular dyad. Thus, stable patterns of dyadic interactions are identified, and the trajectories toward these patterns can be analyzed descriptively. This method also demonstrates the extent to which systemic behavior relies on, or is sensitive to, initial conditions.

Nonlinear dynamics

These methods are derived from highly technical procedures in physics and other sciences and mathematics that aim to measure and model nonlinear phenomena (Abraham, Abraham, & Shaw, 1990; Heath, 2000; Norton, 1995). The simplest of these is nonlinear regression wherein the parameters are exponential functions or the predictive combinations are not only additive. Other applications from this area are those related to chaos theory (Newell & Molenaar, 1998). One can use nonlinear dynamic techniques to find the embedding dimension, entropy, determinism, recurrence, or fractal dimension of any time series of sufficient length and sufficient precision. This class of techniques is typically applied to continuous time-series data (Type 1), which are often physiological. For those developmental psychopathologists who are increasingly collecting this sort of data (e.g., heart rate, skin conductance), this class of methods holds a great deal of promise, particularly if there are reasons to hypothesize nonlinearities. Unfortunately, adequate discussion of this approach is beyond the scope of this paper.

Developmental-Time Measures

Descriptive developmental profile analysis

The empirical work by Thelen and colleagues (e.g., Thelen & Smith, 1994; Thelen & Ulrich, 1991) has been characterized as descriptive in that it is nonparametric, uses descriptive statistics, and often relies heavily on displaying individual developmental profiles graphically. These researchers most often collect continuous time-series data (e.g., number of alternating steps, degree of displacement of foot, proportion of stepping cycle) over repeated occasions across a significant developmental period. They create developmental profiles on a case by case basis and describe the similarities and differences among these profiles. A core concern in this type of analysis is to identify periods of transition during which variability dramatically increases and old behavioral habits dissolve, giving rise to new ones (i.e., from crawling to walking). To complement the individual developmental profiles, they use descriptive statistics such as within subject measures of variance, standard deviations, and correlations to track increases in variability across developmental transition points. Their analyses are generally restricted to continuous (not nominal or categorical) data. In this regard, combining developmental profile analysis with methods that can capture content-specific changes in categorical or ordinal variables may be important. As we suggest later, SSG analysis was developed in part for precisely this purpose (Lewis et al., 1999). Moreover, SSG analysis may help to address the most common criticisms leveled at Thelen and colleagues: the overly "metaphoric" use of DS principles and the lack of quantitative tests that can measure the reliability of developmental patterns (see Lewis & Granic, 1999, for a review; van der Maas, 1995; van Geert, 1997b).

Dynamic growth modeling

On the other side of the descriptive-mathematical continuum is a group of scholars who have pioneered the use of dynamic models in the study of cognitive developmental transitions (e.g., van der Maas, 1998; van der Maas & Molenaar, 1992; van Geert, 1994, 1995, 1997a). The class of techniques advocated by these researchers is often grouped under the heading *nonlinear dynamics,* in reference to the modeling techniques and equations that are associated with this branch of mathematics. These scholars' methods, however, are more circumscribed and relevant to development.

Dynamic growth modeling was developed to simulate change over time (or growth) using logistic difference equations. Van Geert (1994) has used this procedure to model the processes underlying stagelike transitions in the growth of syntactic forms. The basic DS premise of this technique is that development of cognitive capacities is much like the self-organized proliferation of multiple species over the course of evolution. Van Geert models cognitive "growers" that emerge from a complex system of intraindividual and environmental relations. Like the real-time coupled equations described earlier in reference to Gottman's work, the modeling procedure is realized with simulated iterative inputs of amplifying and dampening forces inherent in the system's (i.e., the child's) experiential history combined with current external (contextual) resources and limitations. The growth models depict the kinds of nonlinear developmental profiles predicted by stage theorists (e.g., Piaget and Vygotsky). They also emphasize the use of graphical procedures to plot empirical data from longitudinal studies of children's cognitive skill acquisition in order to match these empirical profiles to the simulations derived from the equations. The mathematical formulations used in these models are common in other disciplines; what makes these models unique is the application of both psychological and DS concepts to identify the mechanisms of growth that replicate observed developmental profiles. Another critical strength of this approach is that the process of developing simulations forces the researcher to specify the null hypothesis explicitly. Thus, the conventional a priori comparison between the hypothesized result and a lack of any effect is replaced by a specific null hypothesis of an alternative pattern of results.

Van Geert (1998c) emphasizes the critical role mathematical modeling plays in developmental research: "In order to find out the implications of theories, they have to be transformed into mathematical models that capture the major dynamic principles of such models and that can be used to explore the range of developmental trajectories under all possible or likely parameter conditions" (p. 155; also see Newtson, 1994; van Geert, 1994). Despite van Geert's concerted efforts to make his approach accessible, these mathematical strategies may have not had a large impact on developmental psychology or developmental psychopathology precisely because of the mathematical procedures that seem daunting to most psychologists.

More importantly, a great deal of the developmental phenomena that researchers are interested in examining are not conducive to this sort of modeling procedure because what they study is not easily quantified along a continuum. Also, regardless of the domain in which this method is applied, and as with all simulation techniques, the correspondence of the parameters in the model with genuine psychological mechanisms is often difficult to evaluate and runs the risk of seeming "arbitrary." Nevertheless, this modeling technique may prove useful for developmental psychopathologists who have some theoretical rationale for positing nonlinear developmental profiles. One possibility, for example, is that clinical prevention efforts may induce nonlinear growth patterns in the development of social skills in some children; using this modeling procedure may provide clues to the underlying mechanisms that support this sort of growth.

Catastrophe modeling

Neo-Piagetian scholars such as van der Maas and Molenaar (1992) have used a particular type of dynamic model, the cusp-catastrophe model, to establish the nonlinear nature of stage transitions. They describe two stages in the modeling procedure: the detection of transitions through a number of criteria or "flags" (Gilmore, 1981; described earlier) and the subsequent fitting of catastrophe models to empirical data. This is a mathematical procedure wherein up to four control parameters can be used to depict discontinuous change in one of seven topological forms (catastrophe models; Thom, 1975; cf. Guastello, 1995). As such, it has some appeal for developmental psychopathologists interested in incorporating insights from developmental stage theories. These models show how each of the possible combinations of control parameters result in different values of a dependent variable. The potential values of the dependent variable are represented on a plane, much like a state space. Nonlinear shifts can be depicted as a fold or curl in the plane showing where behavior changes suddenly rather than continuously. Catastrophes can be thought of as models of nonlinear regressions that include all possible combinations of control parameter values. The plane of the cusp is the space of all possible values of the outcome. As described earlier, the same value of a control parameters can have radically different effects on the collective variable, depending on the history of the system. One major hurdle for applying this method includes the necessity for identifying control parameters. As discussed earlier, psychological control parameters are often difficult to specify and measure. Due to these difficulties, van der Maas and colleagues have gone on to use statistical techniques such as latent class analysis to demonstrate bimodality in a distribution of scores. Bimodality captures statistically what catastrophe modeling captures with equations.

SSG Analysis: A Graphical and Statistical Middle Road

The various DS techniques introduced thus far have considerable potential for addressing some of the analytic challenges faced by developmental psychopathologists. However, we have also pointed out some obstacles for implementing these techniques. In general, most techniques require continuous data, whereas ordinal and categorical variables are more common, especially in observational studies. In addition, many of the techniques are either solely descriptive, precluding researchers from testing the strength and reliability of their findings, or they require complex mathematical procedures that may be inaccessible or irrelevant to most developmental psychopathologists. Recently, a middle ground of hybrid strategies has been developed which combine graphical techniques that capture the descriptive richness of DS concepts with simple statistical procedures that stay true to systems assumptions (Lewis et al., 1999). In this last section of our review, we introduce this new method, SSG analysis. This technique was developed by Lewis and colleagues to address some of the limitations of previous DS methods. It is a graphical and statistical strategy that links the analysis of real- and developmental-time patterns and allows for the identification of individual and group differences. Thus, the flexibility of this methodology may prove to be valuable for developmental psychopathologists. We begin by describing the graphical technique and then move on to the various measures that can be derived from these graphs for statistical analysis. Examples of studies in developmental psychology and developmental psychopathology are provided throughout.

SSG technique

Recall that DS theorists use the concept of a *state space* to represent the range of behavioral habits, or attractors, for a given system. In real time, behavior is conceptualized as moving along a trajectory on this hypothetical landscape, being pulled toward certain attractors and freed from others. Based on these abstract formalizations, Lewis et al. (1999) developed a graphical approach that utilizes observational data and quantifies these data according to two ordinal variables that define the state space for any particular system. Lewis and colleagues have primarily studied intraindividual attractor patterns that emerge and change in the early years of life (e.g., Lewis et al., 1999, in press). The grids they originally developed utilized two ordinal variables (degree of engagement and intensity of distress) that tapped the range of individual infants' potential socioemotional habits. SSGs have also been developed to represent dyadic behavior (e.g., parent–child interactions, peer relations; Granic, Dishion, et al., 2003; Granic & Lamey, 2002; Granic & Patterson, 2001; Hollenstein, 2002). The dyad's trajectory (i.e., the sequence of behavioral states) is plotted as it proceeds in real time on a grid representing all possible behavioral combinations. Much like a scatter plot, one dyad member's (e.g., parent) coded behavior is plotted on the *x* axis and the other member's (e.g., child) behavior is plotted on the *y* axis. Thus, each point on the grid represents a two-event sequence or a simultaneously coded parent–child event (i.e., a dyadic state). A trajectory is drawn through the successive dyadic points in the temporal sequence they were observed. For example, a hypothetical trajectory representing seven conversational turns is presented in Figure 4. Seven successive events are plotted: parent neutral, child neutral, parent hostile, child neutral, parent hostile, child hostile, parent hostile. Note that the labeling of cells follows the *x*/*y* convention such that the first half of the label is the parent's category and the second half of the label is the child's category.

With this temporally sensitive technique, we are able to examine whether behavior clusters in very few or many states (i.e., cells), or regions (i.e., a subset of cells) of the state space. We can also track how long the trajectory remains in some cells but not others, and how quickly it returns or stabilizes in particular cells. If a dyadic trajectory remains in a small number of cells, and makes very few transitions between cells, this system may be thought of as stable, or inflexible. In contrast, a trajectory that moves around to many cells in the state space grid and makes frequent changes between these cells may indicate a highly flexible, or variable, system. We can identify attractors as those cells to which behavior is drawn repeatedly, in which it rests over extended periods, or to which it returns quickly. Moreover, as discussed in the following sections, a range of variables that capture the relative stability of particular attractors may be derived from state space grids and these values can be tested statistically for changes in real and developmental time.

A major advantage of SSGs is that they provide an intuitively appealing way to view complex, interactional behavior; thus they are, first and foremost, a useful tool for exploratory analysis. A recent study that examined the heterogeneity of family interactions with aggressive children may help illustrate this point (Granic & Lamey, 2002). SSGs were used to explore differences in the parent–child interactions of "pure" externalizing children (EXT) and children comorbid (MIXED) for externalizing and internalizing problems. This study is useful not only for demonstrating how the grids work, but also to demonstrate design innovations based on DS principles that are useful with or without SSGs, in this case, a systematic perturbation.

Parents and clinically referred children discussed a problem for 4 min and then tried to "wrap up and end on a good note" in response to a signal (the perturbation). The perturbation was intended to increase the emotional pressure on the dyad, triggering a reorganization of their behavioral system. We hypothesized that, as a function of differences in the underlying structure of their relationships, EXT and MIXED dyads would be differentially sensitive to the perturbation and would reorganize to different parts of the state space. Prior to the perturbation, however, we expected dyads' interactions to look relatively similar. Separate grids were constructed for the pre- and postperturbation interaction sessions. For this study, the lines (trajectories) are less important to notice than the points which show clustering in particular cells. Figure 5 shows an example of an interaction between a pure externalizing child and his parent, pre- and

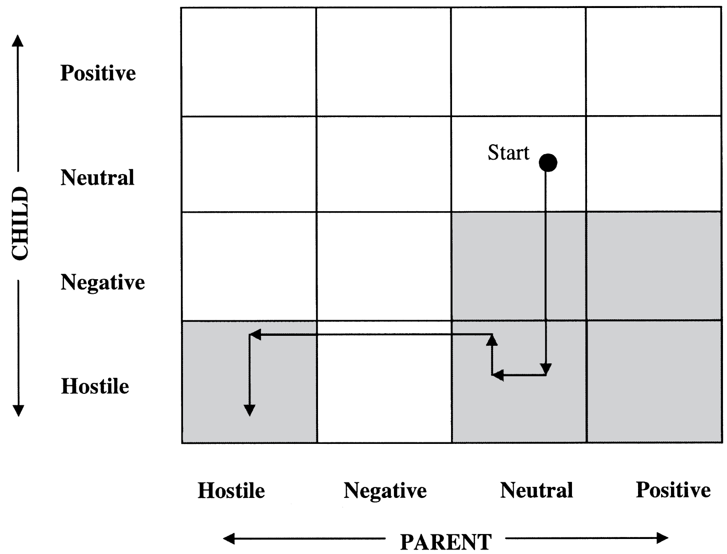

Figure 4. An example of a state space grid with a hypothetical trajectory representing the following seven events: child neutral, parent neutral, child hostile, parent neutral, child hostile, parent hostile, child hostile.

postperturbation. As exemplified in these grids, EXT dyads tended to go to the permissive region (child hostile–parent neutral/positive) of the state space grid, as well as other regions (i.e., mutual neutrality and negativity), before the perturbation. After the perturbation, EXT dyads tended to remain and stabilize in the permissive region. Figure 6 represents the interaction of a MIXED dyad. Similar to EXT dyads, the MIXED dyads occupied the permissive region, as well as other areas, before the perturbation. But in contrast with the EXT group, MIXED dyads tended to move toward the mutual hostility, or mutual negativity, region of the SSG after the perturbation. Granic and Lamey (2002) concluded that the perturbation was a critical design innovation that provided the means by which clinical subtypes could be differentiated.

Another contribution of this study was a more general one: the use of SSGs, with their rich case by case temporal narratives, provided a technique to further parse interaction processes that were previously assumed to represent one coherent pattern. In this case, the coercive process (Patterson, 1982; Patterson et al., 1992; Snyder et al., 1994) was shown to constitute two separate microsocial patterns: two separate attractors on a state space (Granic & Patterson, 2001). Moreover, the conditions under which dyads would be drawn toward one region or the other were found to differ for subtypes. The use of SSGs to uncover heterogeneous processes may be relevant to a variety of phenomena in developmental psychopathology including variability in the real-time unfolding of attachment patterns (cf. Coleman & Watson, 2000), in bullying interactions on the playground (cf. Pepler, Craig, & O'Connell, 1999) and in parent–adolescent interactions during puberty (Granic et al., 2003).

SSG analysis: Real-time measures

SSG patterns can be quantified and used as variables for statistical analyses. Variables that capture the temporal and spatial patterning of behavior have been developed for time-based (e.g., second by second coding) and event-based (e.g., conversational turns) data (Lewis et al., 1999). The same variables may be used regardless of whether the researcher is using the grids to map individual or dyadic behavioral trajectories. We have provided a list of some of these variables but, depending

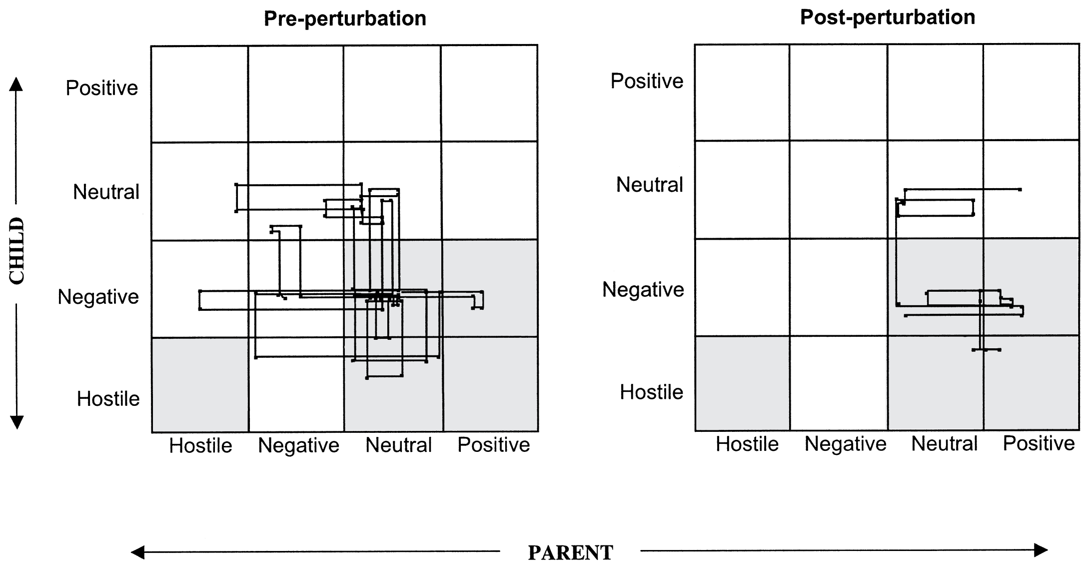

Figure 5. Pre- and postperturbation state space grids for an externalizing dyad.

on the research question, additional ones may be created. Once these parameters have been computed, different types of attractors may be identified and the relative stability of these dynamic states can be measured and subsequently compared in a variety of ways (Lewis et al., 1999, in press).

In general, long durations and/or frequent recurrences of behavior in a particular cell or region suggest an attractor on the state space, and these hypothetical attractors can be compared and tested within individuals across development as well as between individuals. Moreover, parameters describing the stability or variability of behavior across the state space can be calculated for each grid, allowing global, structural comparisons over time, populations, or individuals. Below, as we list the parameters that can be derived from the grids, we refer to Figure 7 for examples. These grids were taken from a study conducted by Lewis and colleagues (1999) that examined the socioemotional coping patterns of infants, and changes in those patterns over a hypothesized stage transition. Originally, these grids were representations of intra-individual behavior plotted according to two ordinal variables, but we have left out the axes labels because they can just as easily represent dyadic behavior and our intention is to provide a generic description that can be adapted to a variety of observational data. It should also be noted that unlike the grids in the Granic and Lamey (2002) study, which used event-based data (conversational turns as observational units), time-based data are plotted in Figure 7; the larger dots in these plots represent longer durations.

The following are parameters that may be computed for each cell in the grid: (a) raw density: cumulative duration (or number of hits) per cell; (b) proportional density: density divided by total episode duration or total number of events; (c) perseverance 1: mean duration (or mean number of consecutive hits) per cell; (d) perseverance 2: longest duration (or longest series of consecutive hits) per cell; (e) return time: latency to return to a cell following an event in that cell. This can be measured in units of time, number of events, or number of unique cells visited en route. For example, in Figure 7, grid B shows a high raw density in cells 2/2 (again, cell labels follow the *x*/*y* convention) and 2/3 and a very low raw density in cell 1/3. In grid C, cell 3/1 shows a high value for perseverance 1 (each time behavior goes to that cell, it tends to stay there for some time) whereas cell 1/1 in that same grid shows a low perseverance value. Finally, grid B shows a very low return time

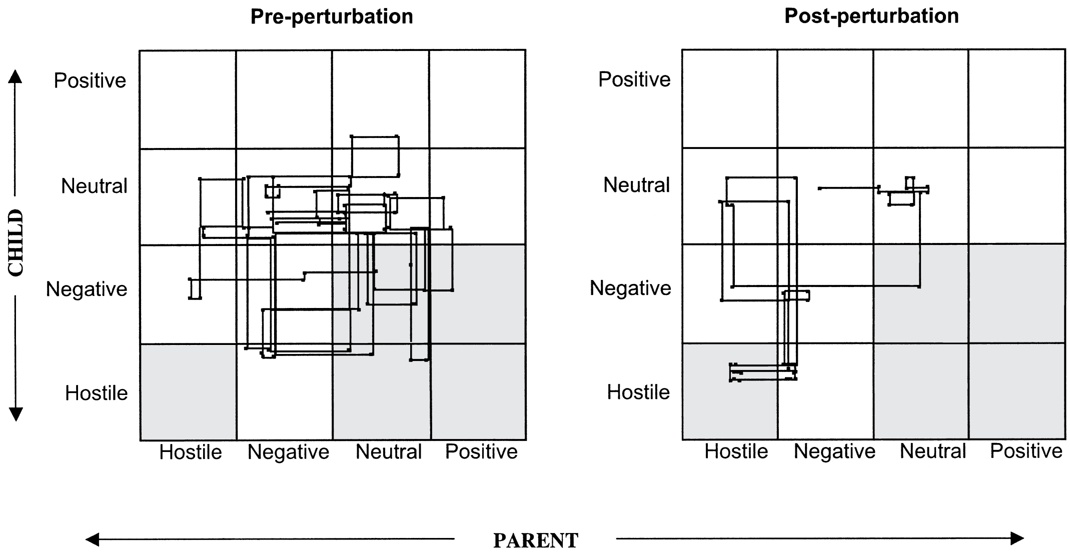

Figure 6. Pre- and postperturbation state space grids for a mixed externalizing and internalizing dyad.

for cell 2/2 (every time behavior leaves that cell, it returns in approximately one turn), but a high return time for grid A, cell 1/0.

There are also several parameters and summary values that can be computed for the entire grid (rather than cell by cell): (a) dispersion: total number of cells visited (with or without controlling for total time or total number of events); (b) fluctuation: number of transitions between cells (with or without controlling for total time or events). Note that fluctuation may be high even though dispersion is low, providing an additional useful parameter (see grid B); (c) stability 1: average of either mean or maximum cell duration values (or events per cell) across all cells. Note that high values indicate overall stability or stickiness of behavioral states; (d) stability 2: mean return time (in time or event units) across all cells. Note that low values indicate overall stability or resilience of behavioral states. Returning to Figure 7, grids A and C show high dispersion compared to grid B, and grid A shows a low stability 1 value compared to grid B.

Developmental psychopathologists are often interested in the relative stability of a certain behavioral pattern or attractor (e.g., depressed mother–infant mutual gaze, coercive interactions). Lewis and colleagues (1999, in press) have developed a number of quantitative strategies for identifying attractors on a SSG. Using the measures previously listed (density, perseverance, return time), attractors can be defined as the cell or cells highest in these values. Once attractor cells are identified, the computed parameters for those cells serve to characterize the strength, endurance, and stability of the attractor for comparison purposes. These comparisons are particularly powerful when they are conducted across developmental time.

SSG analysis: Developmental measures

After computing the parameters that are most relevant for a particular research question, statistical techniques (most of which are quite familiar to developmental psychopathologists) may be applied. We recommend using these statistical procedures in such a way that maintains the integrity of the individual (or dyadic) case (e.g., curve estimation procedures, cluster analysis). However, multivariate analyses, including analyses of variance (ANOVAs), regressions, and structural equation modeling, can just as easily be run on the grid variables.

One example of a developmental SSG anal-

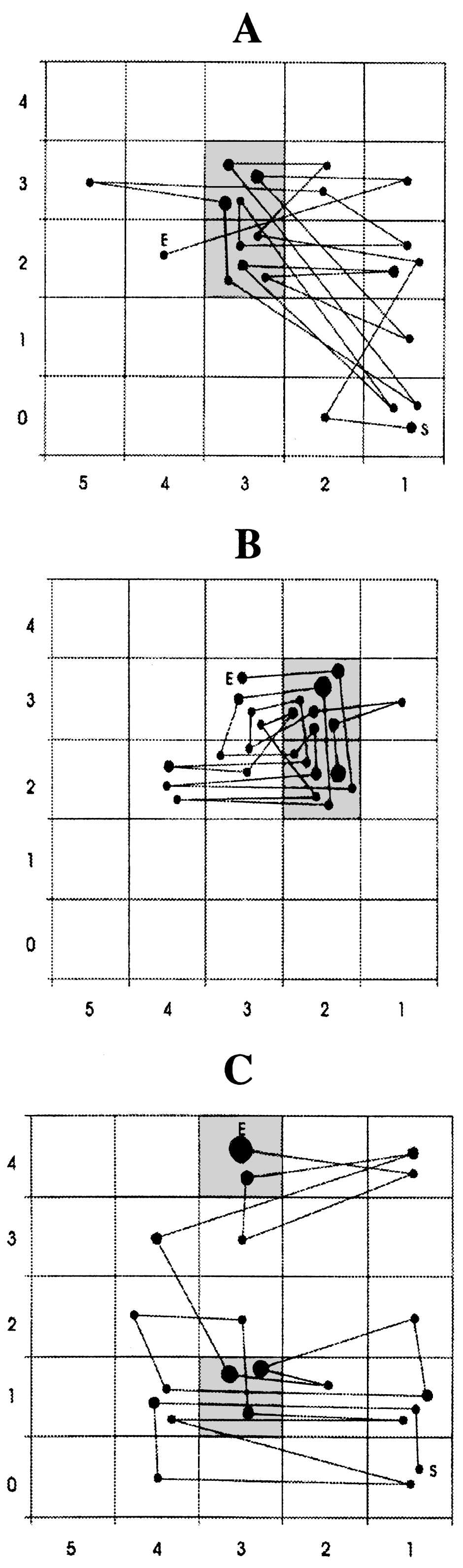

Figure 7. Examples of three state space grids from Lewis et al. (1999).

ysis comes from a recently completed study by Lewis et al. (in press). These researchers were examining a developmental transition in late infancy which was hypothesized to exhibit the properties of a phase transition (i.e., increased variability in real-time patterns, a breakdown of old attractors and the emergence of new ones over developmental time). The general hypothesis that guided this study and similar DS-inspired studies that focus on phase transitions is presented in Figure 8. Infants were videotaped in frustrating situations on 12 monthly visits before, during, and after a hypothesized transition point at 18–20 months. SSGs were constructed for each episode and grid to grid differences were compared over age. As predicted, grid to grid differences were greater during the transitional period than before or after, indicating a developmental reorganization of behavioral responses to negative emotion. Also, new attractors appeared more frequently during the period of transition than at other ages.

Lewis and colleagues (in press) provide two techniques to measure *within-subject* differences among SSGs. First, grid to grid Euclidian distance scores yield a global metric of the difference in behavioral landscapes from month to month, based on the sum of squared differences across all cells. For each grid cell, the difference in values over two consecutive months is calculated, then squared, and then these values are summed for all cells. Next, the square root of this sum is taken as the distance score between the two grids.

A second developmental analysis they explored was a cluster analysis technique to look at changes over time. The first step is to categorize the grids by entering all grids into a *k* means cluster analysis. The most parsimonious cluster solution is chosen (based on preset criteria). The cluster score for each grid is then recorded. Visual inspection of the grids is recommended at this point to ensure that the same cluster scores look alike topographically, having similar duration values for many of the same cells. Developmental continuity would thus be indicated by a sequence of months (2 or more) with the same cluster score, and developmental variability would be indicated by month to month change in cluster membership.

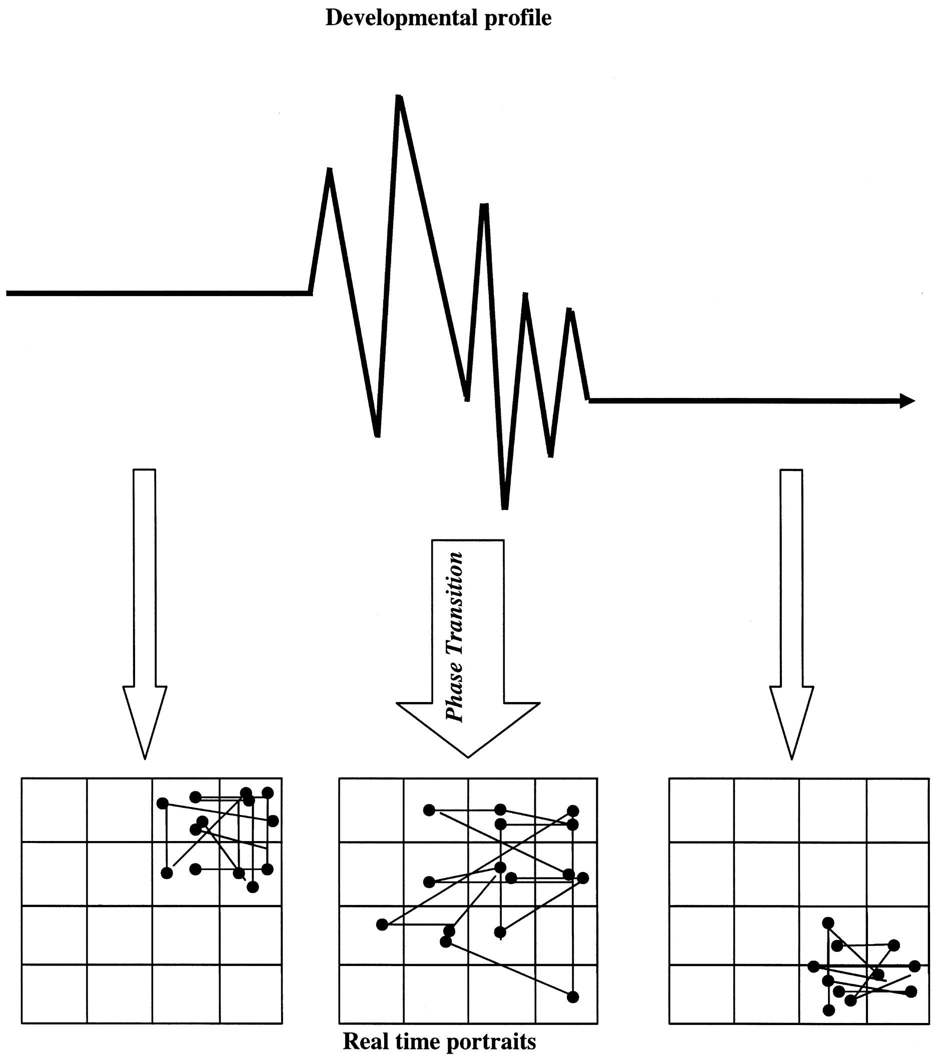

Figure 8. The model of a developmental phase transition; developmental phase transitions are periods of fluctuation in developmental time and increased variability in real time.

Another method of analyzing changes in SSG patterns over developmental time comes from a recent study that examined changes in the structure of family interactions during the early adolescent transition period (Granic, Dishion, et al., 2003; Granic, Hollenstein, et al., 2003). Following Lewis and colleagues' (1999) developmental hypothesis, we examined whether early adolescence (age 13–14 for boys) constitutes a developmental transition (a period of reorganization) marked by a peak in the variability of family interactions; before and after this period, interactions were expected to be stable. Longitudinal observational data were collected in five waves prior to, during, and after the transition period. One hundred forty-nine parents and boys were observed problem solving at 9–10 years old, and every 2 years thereafter until they were 17–18 years old. Based on this data, SSGs were constructed for all families across all waves. Two variables indexing the variability of the interactions (fluctuation and stability) were derived from these grids. A repeated measures ANOVA on these variables revealed a significant quadratic effect. To ensure that these results were not just significant on the group level, but also characterized the majority of families in the sample, the wave at which flexibility peaked (when fluctuation was highest and stability was lowest) was recorded. Results revealed that the majority of families showed a peak in variability in the middle wave, and hardly any families peaked in the first or last wave.

From these examples, it should be clear that any other statistical tool that has been developed to measure growth or change over time can be combined with SSG analysis. The important difference in these variables (compared to questionnaire data, for instance) is that they capture temporal patterns as they unfold over time. Thus, for instance, a researcher might hypothesize that children comorbid for externalizing and internalizing problems will be more likely than pure externalizing children to develop increasingly hostile and rigid interactions with their parents. This study might include collecting observational data of parent–child interactions with these two types of children and parents every year for 5 years. By using SSGs, the strength of the mutually hostile attractor can be assessed at each observational wave (e.g., return time to mutually hostile cell; stability of cell), but so can the mutually positive attractor, and fluctuation between the two states and others (thus addressing the potential for multistable state space patterns). Dispersion and fluctuation variables can also be computed, in order to examine whether, over the course of development, comorbid dyads' behavioral repertoires become more rigid, leaving less options available to them. These variables can subsequently be entered into structural equation modeling procedures that control for measurement error and account for variance due to clinical subtype, gender, and ethnicity. In addition, different growth profiles (e.g., for the strength of hostile versus positive attractors, dispersion and stability measures) can be examined for each dyad type.

Although the SSG method is clearly still in its early stages of development, we are encouraged by its potential. One of the important advantages to this technique is its inherent flexibility. At the very least, it is a visual, exploratory tool to develop and refine hypotheses. Researchers are not limited to using continuous time series, as is the case with many other DS methods. Categorical and ordinal data are also appropriate for this type of analysis. Also, the grids are malleable in that they can represent systemic behavior on the individual as well as dyadic level. In addition to the examples mentioned above, changes in peer, romantic couples, and sibling interactions, for example, can easily be tracked using SSGs. In fact, apart from the difficulties in visually representing the data, the variables derived from the grids can be extended past the two dimensions on which we have focused. For instance, triadic family interactions or family interactions with siblings and parents can be measured for attractor strengths, fluctuations, and so on. Another benefit of this approach is the extent to which it remains "user friendly" and does not require expertise in mathematical modeling.

Implications of DS Methods for Clinical Research

Because DS methods are specifically designed to capture change processes, and because the study of psychopathology often breaks down into the study of individual patterning, one of the most exciting potential applications of SSGs may be in clinical research. Specifically, this methodology may be particularly well suited for the study of heterogeneous change processes that may underlie treatment progress and outcome. Focusing for the moment on aggressive children, a great deal of research has shown that family-based treatments targeting coercive interactions can decrease levels of aggression in children, but very little is known about how these treatments work (Kazdin, 2000, 2001, 2002). The SSG methodology should be able to provide a microsocial, process-level account of how family and peer relationships change over the course of treatment and follow-up. In addition to identifying content-specific changes (e.g., less hostility and more mutual positivity in parent–child interactions), this method has the potential to tap structural changes associated with treatment success. For example, as a result of treatment, do parent–child dyads move more quickly from a hostile, conflictual interaction into a reparative one? Do they develop several alternative problem-solving strategies that they can maneuver through more flexibly?

The parameters described earlier are easily amenable to this type of analysis. From a developmental psychopathology perspective, psychopathology "represent[s] diminished flexibility and constrictions in the affective, cognitive, and behavioral correlates of adaptational patterns" (Overton & Horowitz, 1991, p. 3). With the application of SSGs, it is possible to test this type of structural hypothesis. It may be that those youth who benefit from treatment will not abandon negative behavioral habits but soften them, through the development of a less rigid, more flexible behavioral repertoire. This approach can specify at what point in the interaction dyads become hostile, how long they maintain hostile exchanges, the ease with which they "escape" them, the range of alternative patterns available to them, and the tendency to return to hostility. Dispersion, stability, and fluctuation measures can be computed and changes in any of these parameters can then be tracked over the course of treatment and follow-up, to assess the hypothesis of increased behavioral flexibility in relation to successful interventions. Instead of relying on central tendency measures (e.g., means and correlations), this technique maintains the temporal integrity of real-time interactions and, thus, can better capture some of the microsocial processes hypothesized to be most important.

Conclusion

From the beginning of its establishment as a discipline, one of the core priorities in developmental psychopathology has been methodological diversity (e.g., Cicchetti & Cohen, 1995a, 1995b; Cummings et al., 2000; Richters, 1997). One reason for encouraging this analytic pluralism is the recognition of the disparity between systems-based models of developmental psychopathology and the inadequate methodological tools that are available to test them (Richters, 1997). We have argued that DS approaches to development offer research methods that show greater fidelity to the complex, heterogeneous, temporal nature of developmental phenomena. Clearly no set of analytic methods can address the mismatch of methods and models entirely; thus, we are not arguing for the complete abandonment of well-established techniques. Instead, our purpose in providing a survey of DS methods is to encourage developmental psychopathologists to begin examining empirically questions that may have previously seemed out of analytic reach.

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