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The Spirit Is Willing: Nonlinearity, Bifurcations, and Mental Control

Keith Warren,[1,4] Julien C. Sprott,[2] and Raymond C. Hawkins[3]

In recent years there has been considerable interest in the construction of nonlinear models of the dynamics of human behavior. In this exploratory article we argue that attempts at controlling problematic thoughts, emotions, or behaviors can lead to nonlinearity in mental/behavioral dynamics. We illustrate our model by fitting threshold autoregression models to self-recorded time series of the daily highs in intensity of anxiety and obsessive ruminations, kept by an individual in therapy for this problem. In our discussion, we raise the possibility that bifurcations that occur in this nonlinear model may offer insight into mental control paradoxes.

KEY WORDS: chaos theory; self-control; emotional control; time series; generalized anxiety disorder.

In recent years, social science researchers who focus on nonlinear dynamics have shown an increasing interest in the construction and testing of nonlinear mathematical models (Brock & Durlauf, 2000; Epstein, 1997; Guastello, 1995; Hansen, 2000). This is a welcome development, since a nonlinear mathematical model is often more useful in building theory than simple evidence of deterministic chaos (Abarbanel, 1996). For instance, the bifurcation structures inherent in even simple nonlinear systems offer the possibility of understanding and anticipating sudden changes in human behavior (Berecz, 1992; Brock & Durlauf, 1999; Epstein, 1997; Guastello, 1995). Nonlinear dynamical models might also serve to connect differing areas of

[1]College of Social Work, The Ohio State University.
[2]Department of Physics, University of Wisconsin-Madison.
[3]Department of Psychology, The University of Texas at Austin.
[4]Correspondence should be directed to Keith Warren, Ph.D., Ohio State University, College of Social Work, 1947 College Road, Columbus, OH 43210.

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social science inquiry, since similar dynamics might occur in very different contexts (Vallacher & Nowak, 1994).

In this article we suggest a simple model of nonlinearity that arises in the course of efforts to control problematic thoughts, behaviors and emotions. We then illustrate the model using two time series collected in the course of clinical work with an adult male who suffered from anxiety and obsessive ruminations. Our discussion will focus on the possibility that a nonlinear model of mental control might further our understanding of mental control paradoxes.

A NONLINEAR MODEL OF MENTAL AND BEHAVIORAL CONTROL

Suppose that an individual wants to control the level of a problematic thought, emotion, or behavior. For illustration, we will assume that the particular problem is chronic anxiety. If there is an increase in anxiety, the individual will soon try to decrease it by thinking of distracting thoughts or engaging in a distracting activity (Wegner, 1989). The individual's attempts to control his anxiety should therefore come in response to the most recent changes in the level of anxiety. If these attempts are successful, at least in the short run, we can model the process of anxiety control using a difference equation that links changes in anxiety from one time period to the next:

$$\Delta A_t = F(\Delta A_{t-1}) \tag{1}$$

In this equation, $\Delta A_t = A_t - A_{t-1}$, or the most recent change in the level of anxiety, while $\Delta A_{t-1} = A_{t-1} - A_{t-2}$, the previous change in the level of anxiety. The equation simply says that the most recent change in the level of anxiety comes in response to, and therefore is a function of, the previous change in the level of anxiety.[5]

The function itself might be linear or nonlinear. Is there any reason for expecting nonlinearity in this equation? Let us again take the case of anxiety. Most people can exert at least short-term control over anxiety, perhaps by using distracter strategies (Wegner, 1989), by engaging in a relaxation exercise that might reasonably be expected to lower anxiety (Forgays & Forgays, 1992), or by changing the behavior that is leading to anxiety (Carver & Scheier, 1992). However, any attempt to control anxiety would carry a certain cost in terms of time, effort and attention, and the goal of controlling

[5]There is a significant tradition within social psychology of models that suggest that individuals react to changes in their condition. This tradition would include Helson's (1965) and Parducci's (1995) models of judgment of subjective well-being, as well as Carver and Scheir's (1999) and Hsee and Abelson's (1991) models of affect as a function of rate of progress toward a goal.

anxiety will coexist with other goals (Carver & Scheier, 1999). An individual who spends eight hours per day performing relaxation exercises may feel little anxiety, but the attainment of other goals is likely to suffer.

It therefore seems reasonable to expect an individual to vary the intensity of his or her efforts at control, depending on whether the investment in control seems worth the gains from control. In the case of anxiety, a large increase in the level of anxiety ought to be more threatening than a small increase in anxiety, assuming that both occur over the same period of time (Hsee & Abelson, 1991), and should lead to a more intense effort at control.

Such a situation can be described with a dynamical equation of the following form:

$$\Delta A_t = a + b\Delta A_{t-1} \text{ if } \Delta A_{t-1} \text{ falls below the threshold value}$$
$$\Delta A_t = c - d\Delta A_{t-1} \text{ if } \Delta A_{t-1} \text{ falls above the threshold value} \qquad (2)$$

This is known as a self-exciting threshold autoregression (SETAR) (Tong, 1990) model. ΔA gives the rate of change of the thought or affect that the person wishes to control, while the subscript, t or t-1, indicates the time period. If there is a large enough increase in the person's anxiety in one time period, he or she uses a control strategy to lower it in the next. Thus, this model includes a negative coefficient above the threshold.

Of course, other scenarios are possible. For instance, an individual might put a small amount of effort into controlling anxiety at a low level, but more after a sudden increase. This would lead to a threshold model with negative coefficients both above and below the threshold, but the coefficient above the threshold would be more negative—i.e., larger in absolute value.

The nonlinear model that we are proposing has no inherent time scale. It might apply to time frames of minutes to an hour or so, as one struggles to suppress problematic thoughts, but it could also apply to time frames of a day or even a week. Imagine that an individual who suffers from anxiety takes time to exercise the day after any increase, as a means of stress management. This could produce a cycle of increase-decrease-increase on a daily basis. Similar cycles could happen on a weekly basis, and so on.[6]

A similar analysis might apply to a wide range of problematic thoughts, emotions and behaviors. For instance, a sudden increase in ruminations could disrupt an individual's life, and could therefore lead to increased efforts at control. If this model is reasonable, threshold nonlinearity should appear in the first difference of time series of a variety of problematic conditions.

[6]However, psychological limitations will impose a time scale. For instance, we would not expect this model to apply at time scales too small to allow evaluation of, and reaction to, a thought, emotion, or behavior.

We will illustrate this by analyzing two self-reported time series of levels of anxiety and obsessive ruminations.

AN ILLUSTRATION OF THE MODEL

Data

The data to be used in illustrating this model consists of ratings of the intensity of anxiety and obsessive thoughts kept by an adult male over a period of 274 days. The participant was in therapy for anxiety at the time, and carried a DSM Axis I diagnosis of generalized anxiety disorder and an Axis II diagnosis of personality disorder NOS with obsessional and avoidant traits. The participant experienced both anxiety and obsessive ruminations about his own mental and physical health, work status, ability to compete as an amateur athlete and body image. For each day the participant drew one line that tracked the intensity of his anxiety, beginning in the morning when he woke and ending when he went to bed at night, on a self-anchored scale ranging from one to ten. He drew a second line that tracked the intensity of his obsessive thoughts.

This tracking system did not specify the nature of the participant's thoughts or the sources of his anxiety. While the participant did make occasional qualitative notes on his thoughts and on events that seemed to increase or decrease the level of his anxiety, they were too uncommon to be of use in this analysis.

Analysis of data in time frames shorter than a day was complicated by the participant's inability to record the intensity of his anxiety or obsessive thoughts while sleeping; thus, approximately one third of possible data points in any time frame shorter than a day would be missing. We therefore recorded the highest daily levels of anxiety and obsessive ruminations over the 274 days of the time series. It was reasoned that the participant would be most likely to remember, and react to, the most intense level of his problematic thoughts and behaviors on the previous day. These highest values then became our time series of daily values. The two time series of daily high levels of anxiety and obsessive ruminations are shown in Fig. 1. All values have been rounded off to the nearest .5. Descriptive statistics are given in Table 1. The values in the time series of daily high levels of anxiety appear to be normally distributed, while those in the time series of daily high intensity of obsessive ruminations show positive skew and kurtosis.

Finally, the first difference of each data set was taken before analysis. This was consistent with our model of reactions to changes in the level of

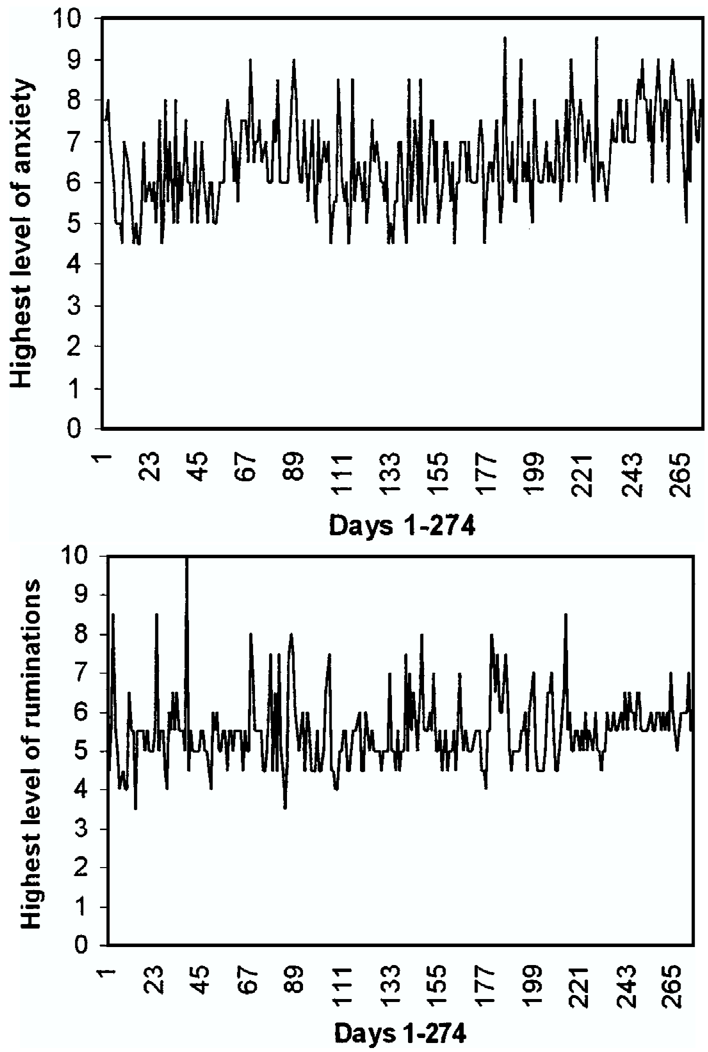

Fig. 1. Daily high levels of anxiety and obsessive ruminations.

Table 1. Descriptive Statistics for Daily High Levels of Anxiety and Obsessive Ruminations

Variable	Mean	Standard deviation	Range	Skew	Standard error of skew	Kurtosis	Standard error of Kurtosis
Anxiety	6.54	1.12	5.00	0.27	0.15	−0.53	0.29
Obsessive ruminations	5.49	0.93	6.50	1.25	0.15	2.71	0.29

problematic emotions and thoughts. The two first-differenced time series are shown in Fig. 2, and descriptive statistics for the first-differenced time series are given in Table 2.

Methodology

The specific model that we have proposed, two linear regimes separated by a threshold, is known as a self-exciting threshold autoregression model, or a SETAR (Hansen, 1999; Hansen, 1997; Tong, 1990). The form of the statistical model is simply equation 1 with unspecified variables or coefficients, allowing for the possibility of more than one time lag and adding an error term e of gaussian distributed random shocks to the model:

$$\Delta X_t = a + b_1 \Delta X_{t-1} + \cdots + b_n \Delta X_{t-n} + e \quad \text{if } X_{t-1} \text{ falls below the threshold value}$$

$$\Delta X_t = c + d_1 \Delta X_{t-1} + \cdots + d_n \Delta X_{t-n} + e \quad \text{if } X_{t-1} \text{ falls above the threshold value} \tag{3}$$

The values of the parameters a, b, c, and d, along with the threshold value, are found by running a series of ordinary least squares regressions over a range of threshold values and choosing the value that minimizes the residual variance (Hansen, 1997).

Table 2. Descriptive Statistics for Daily Changes in the Highest Level of Anxiety and Obsessive Ruminations

Variable	Mean	Standard deviation	Range	Skew	Standard error of skew	Kurtosis	Standard error of Kurtosis
Anxiety	0	1.37	7.50	−0.32	0.15	0.54	0.29
Obsessive ruminations	0	1.17	10.50	0.08	0.15	3.12	0.29

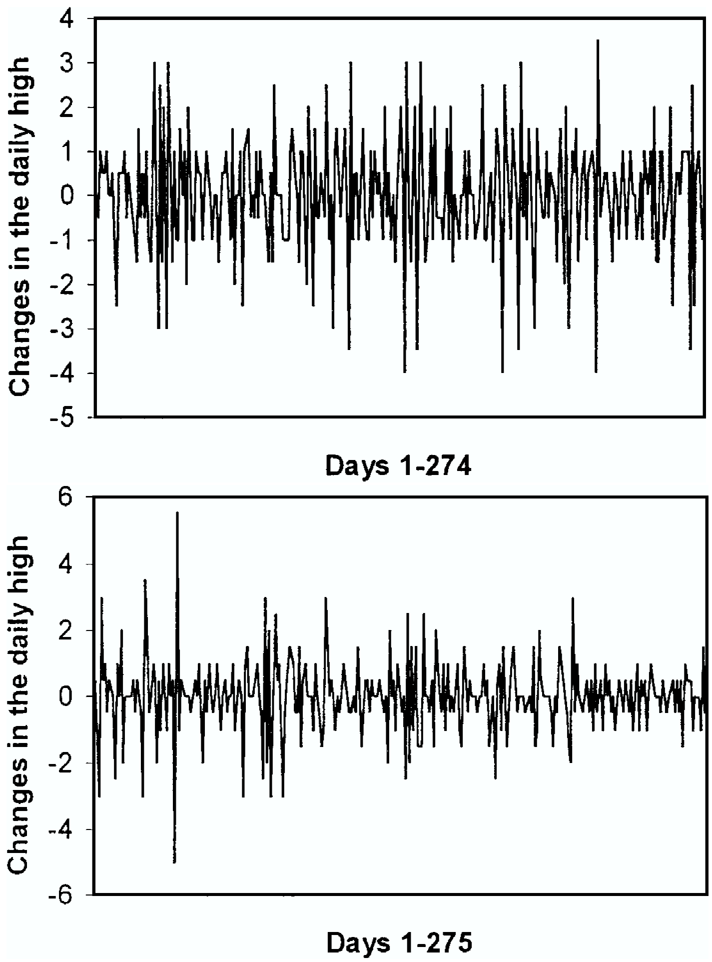

Fig. 2. Changes in the daily high levels of anxiety and obsessive ruminations.

We tested the model against the null hypothesis of a linear autoregression (AR) model (Hansen, 1999; Hansen, 1997):

$$\Delta X_t = a + b_1 \Delta X_{t-1} + \cdots + b_n \Delta X_{t-n} + e \qquad (4)$$

In the linear model, it is also possible to include multiple time lags. In other words, both linear and nonlinear models allow for the possibility that the value of ΔX during the current time period depends on the values during several previous time periods.

Table 3. Evidence of Nonlinearity in Daily Changes in Self-Reported Intensity of Anxiety and Ruminations

Daily changes in intensity of anxiety[a]		
Parameter	Parameter estimate	Standard error
	Regime 1, $X_{t-1} \leq 0$	
Constant	0.15	0.14
$X(t-1)$	−0.25	0.10
	Regime 2, $X_{t-1} > 0$	
Constant	0.53	0.20
$X(t-1)$	−0.82	0.10
Daily changes in intensity of ruminations[b]		
	Regime 1, $X_{t-1} \leq 1.5$	
Constant	0.09	0.07
$X(t-1)$	−0.26	0.07
	Regime 2, $X_{t-1} > 1.5$	
Constant	1.26	0.80
$X(t-1)$	−1.20	0.30

[a]Threshold estimate 0; 95% confidence interval: −2.5, 3.0; joint $R^2 = .24$; F-test for no threshold: 12.04; P value = .01.
[b]Threshold estimate: 1.5; 95% confidence interval: −1.5, 2.5; joint $R^2 = .25$; F-test for no threshold: 21.69; P value = .00.

The linear autoregression model in equation 3 is effectively a SETAR model with only one regime—a SETAR(1). Thus, equation 4, the AR model or SETAR(1), is nested inside of equation 3, the SETAR(2). We can test for the presence of a threshold, and therefore nonlinearity, by testing the SETAR(2) against the SETAR(1), since they are nested models (Hansen, 1999).

However, since the threshold is not identified under the null hypothesis of SETAR(1), the asymptotic distribution of F under the null is unknown (Hansen, 1996; Hansen, 1997). Because of this a parametric bootstrap procedure is used to construct the null distribution of F. In this procedure residuals under both the null (SETAR(1)) hypothesis and alternative (SETAR(2)) hypothesis are simulated and used to construct a bootstrap F distribution (Hansen, 1996; Hansen, 1997). This, in turn, means that the relationship between F and p values will differ from that in a standard F distribution table.[7]

Results

The results of this illustrative nonlinear time series analysis are summarized in Table 3. The table details two SETAR(2) models, one for the first

[7]The program used to fit the models in this paper, along with several of the referenced papers and other work on threshold autoregression models, can be found at http://www.ssc.wisc.edu/~bhansen/.

difference of the highest daily level of anxiety and one for the first difference of the highest daily level of obsessive ruminations. For both time series, the model gives separate parameter estimates for Regime 1, values below the threshold, and Regime 2, values above the threshold. The reported joint R^2 values ($R^2 = .24$ for the time series of changes in level of anxiety, $R^2 = .25$ for the time series of changes in level of obsessive ruminations) apply to the model as a whole, the threshold and the parameters both above and below the threshold. For each time series, the threshold model yields a statistically significant improvement in fit over a linear autoregression ($F = 12.04$, $p < .01$ for the time series of changes in level of anxiety, $F = 21.69$, $p < .01$ for the time series of changes in level of obsessive ruminations).

In each case, the threshold occurs on the first lag of the data. This is what one would intuitively expect; it would appear to be more likely that yesterday's change in problem behavior, rather than the change two or three days ago, would determine today's reaction. Also in each case, the slope parameter above the threshold is more sharply negative than the one below it. This is consistent with the scenario posed earlier, in which rapid increases in anxiety or ruminations force efforts at control.[8]

We have juxtaposed the two SETAR(2) models over scatterplots of data in Fig. 3. In creating these scatterplots we added a small amount of gaussian noise to the data. This was done because the original rounding of the data to the nearest 0.5 left many data points juxtaposed. The addition of the gaussian noise smears the data points around the rounded values, allowing a view of the density of the points.

DISCUSSION

In this section we would like to discuss some implications of the model we have sketched. We must emphasize that empirical support for this model is currently drawn from a small number of time series. In addition to the current article, the model has been applied to the behaviors of several adolescent sex offenders (Warren & Knox, 2000) and one individual carrying a diagnosis of substance abuse (Warren, Hawkins & Sprott, 2000). Empirical support for this model is, therefore, very limited at this time.

The model itself is obviously a highly simplified account of a complex process. Like any statistical model, it yields values that give an estimate of what is likely to be a fuzzy underlying reality. It seems unrealistic, for instance, to suppose that the threshold remains constant at different times and in different environments. It might be more realistic to think

[8] It should be mentioned that this is not simple regression to the mean. In a time series context, regression to the mean is a linear, negative relationship between one time period and the next.

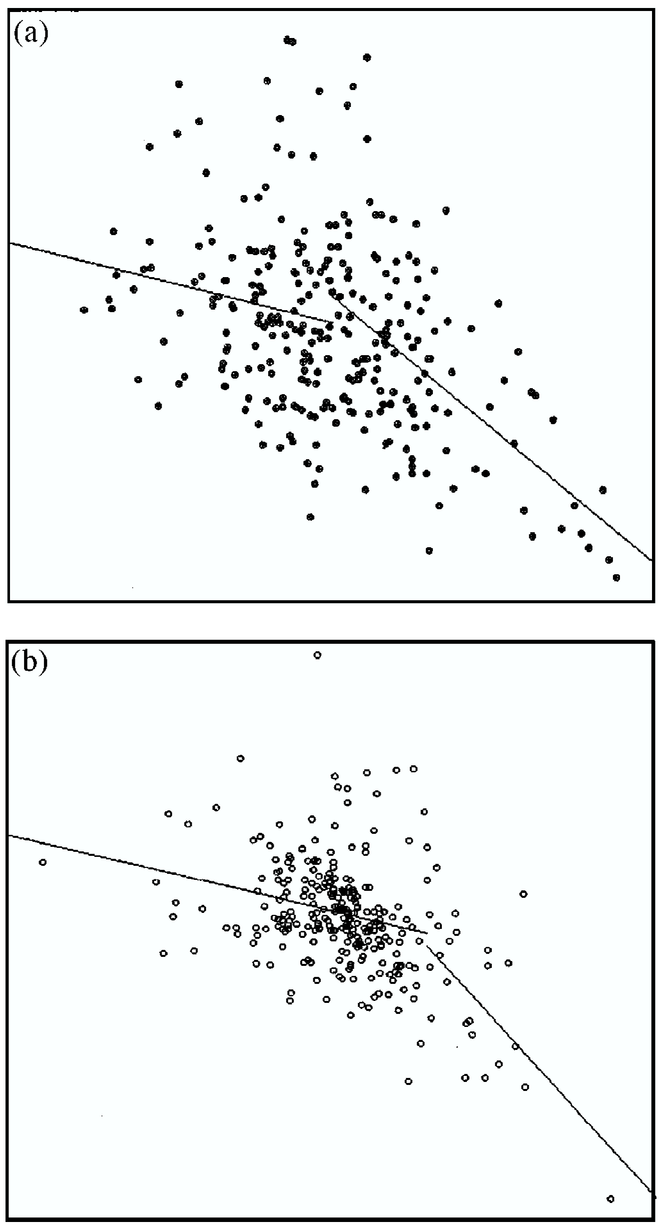

Fig. 3. Overlay of SETAR(2) parameters on time series of daily changes in anxiety (a) and ruminations (b).

of the threshold as being an average of a large number of decisions on when and how to attempt to control anxiety that occurred over a period of months.

On the other hand, simplicity has its advantages when trying to think about complex systems (Bar-Yam, 1997; Epstein, 1997), and we believe that a simple model such as this can provide a valuable lens through which to examine a complex process. In particular, we think that this model might further our understanding of mental control paradoxes, those times when efforts at mental control backfire, leading to an increase in intensity of the emotion, behavior or thought that the individual is attempting to control (Martin & Tesser, 1996; Wegner, 1994, 1989).

Several theories have been advanced as to why a mental control paradox could occur. Martin and Tesser (1996) argue that ruminations occur as a side effect of goal frustration. Goal attainment involves thinking of the goal and ways of attaining it. If something frustrates goal attainment, thoughts pertaining to the goal are likely to continue. Wegner's (1994) ironic process model posits that mental control requires both a control process that seeks to create the desired state, and a monitoring process that tells whether the desired state has been obtained. However, the monitoring and control processes often operate at cross-purposes. While the mental control process is conscious, the monitoring process occurs outside of conscious control. Once the mental control process has implemented the desired mental state, the monitoring process continues searching for the undesired mental state, so as to be sure that it is really gone. The upshot is that the unconscious monitoring process tends to bring the undesired mental state back to awareness (Wegner, 1994; Wegner & Wenzlaff, 1996).

We would like to suggest that mental control paradoxes might be fruitfully modeled as bifurcations that arise in a nonlinear process of mental control. A brief review of the role that equilibrium points play in the dynamics of threshold models will be useful in illustrating how a nonlinear model of mental control paradoxes would work.

A threshold difference equation will have multiple equilibrium points. The SETAR(2) used in this paper has two of them, one for each regime. However, the system may not be able to reach both points, because the threshold may lie below the lower equilibrium point or above the higher one. When the threshold passes an equilibrium point, a global bifurcation occurs. This can lead to three possible outcomes: a sudden change in the equilibrium value, periodic fluctuations or chaotic behavior. The actual outcome depends on the stability of the two points, which one the threshold passes, and in which direction the threshold is going.

As an example, we can consider the fitted model of fluctuations in rumination presented in Table 2. For the moment, we can treat the model as a deterministic equation:

$$\begin{aligned}\Delta X_t &= .09 - .26\Delta X_{t-1} \quad \text{if } \Delta X_{t-1} \le 1.5\\ \Delta X_t &= 1.26 - 1.20\Delta X_{t-1} \quad \text{if } \Delta X_{t-1} > 1.5\end{aligned} \tag{5}$$

We can solve for the equilibrium points by setting the values to be equal from one time period to the next and using elementary algebra:

$$\begin{aligned}\Delta X &= .09 - .26\Delta X \cong .07 \quad \text{if } \Delta X_{t-1} \le 1.5\\ \Delta X &= 1.26 - 1.20\Delta X \cong .57 \quad \text{if } \Delta X_{t-1} > 1.5\end{aligned} \tag{6}$$

In this case, all values will approach the stable equilibrium point below the threshold as the equation is iterated. Since we are modeling rates of change in the intensity of ruminations, this point corresponds to a tendency for the intensity of ruminations to rise very slowly.

But if the individual decides that any rise at all is unacceptable, the control regime will begin at a threshold of zero, below the lower of the two equilibrium points. In the model, this would bring about a bifurcation into either a periodic or a chaotic regime, which would lead to a series of spikes in the intensity of ruminations. Thus, if this model is correct, an attempt to reduce the intensity of ruminations could lead instead to large fluctuations in that intensity.

The discussion thus far has assumed a deterministic model of human behavior. In a noisy, stochastic model, a nonlinear system can either dampen or amplify the noise, depending on the value of the model parameters and the amount of noise (Deissler & Farmer, 1992). To simulate stochastic dynamics, we will use the model of fluctuations in ruminations, again assuming that the threshold occurs at a value of 1.5:

$$\begin{aligned}\Delta X_t &= .09 - .26\Delta X_{t-1} + e \quad \text{if } \Delta X_{t-1} \le 1.5\\ \Delta X_t &= 1.26 - 1.20\Delta X_{t-1} + e \quad \text{if } \Delta X_{t-1} > 1.5\end{aligned} \tag{7}$$

We can assume that *e*, the error term, consists of gaussian white noise with a standard deviation of 0.5. The deterministic skeleton of the equation (Tong, 1990) has the same two equilibrium points as before. Random deviations will approach a stable equilibrium point and recede from an unstable equilibrium point.

In the initial case, the threshold of 1.5 is well above the upper equilibrium point. Output values cluster in a small ball around the lower equilibrium point (Fig. 4). This system behaves very much like a noisy but stable linear system; the introduced noise pushes values away from the stable equilibrium point, but the point pulls them back.

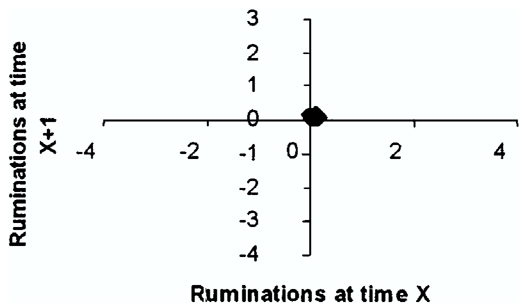

Fig. 4. A nonlinear system that acts to damp noise.

When we lower the value of the threshold to 0, a very different and much larger attractor appears (Fig. 5). In this case, the introduced noise can push the output values across the threshold. When this happens, the unstable equilibrium point above the threshold amplifies the noise that has been introduced into the system. This amplification forms a stochastic analog of the deterministic bifurcation that we observed earlier. The nonlinear system has gone from acting as a noise damper to acting as a noise amplifier (Deissler & Farmer, 1992). Just as in the deterministic case, the bifurcation occurs when the threshold of the control regime is lowered.

Once the added noise pushes the output of the system across the threshold, the nonlinearity tends to amplify the stochastic fluctuations. Thus, an amplification effect could occur within the model because the amount of added noise increased as well as because the threshold of the deterministic skeleton fell. In clinical terms, this might correspond to either a rise in environmental stress or a lowering of the point at which an increase in ruminations kicks off an increased attempt at control.

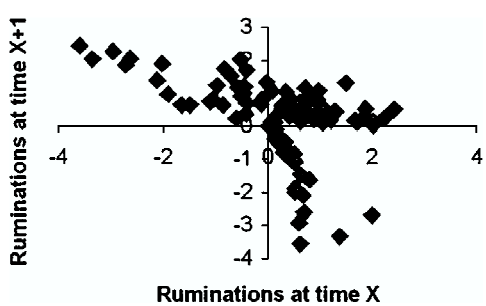

Fig. 5. A nonlinear system that acts to amplify noise.

This model would complement the Martin and Tesser (1996) and Wegner (1994) models in at least two ways. First, while these models of mental control paradoxes explain why thoughts might continue after goal frustration, or return after an attempt at suppression, they do not explain why an actual increase in the number of unwanted thoughts should occur. Such increases, which are a common finding (Wegner & Gold, 1995; Wegner, Schneider, Carter & White, 1987), occur naturally in a nonlinear model.

Second, because it is not tied to a single problem or time frame, the nonlinear model is rather general and could be amenable to empirical testing in clinical settings. One could fit a number of threshold autoregression models to clinical time series and test to see whether the threshold values predicted either the volatility of the time series or the absolute number of problem behaviors. Such a study would be of value, since one reason for the current interest in mental control paradoxes is their potential importance in explaining clinical phenomena such as client resistance to change (Kirsch & Lynn, 1999). Evidence of mental control paradoxes in clinical settings would be a significant step toward such an explanation.

CONCLUSION

Any research program must ultimately demonstrate its own usefulness, either in extending knowledge or in leading to practical applications. The question of usefulness is of particular importance to the community of researchers who seek to apply nonlinear dynamics to the social science; the framework of nonlinear dynamics is new to most social scientists, and its value is not always obvious.

One attempt to answer the question of usefulness has been the suggestion of Vallacher and Nowak (1994) that nonlinear dynamics could serve to connect apparently disparate areas of social psychological inquiry, thus leading to greater unity. We believe that researchers will find that similar dynamical phenomena will occur as individuals attempt to control apparently unrelated problem behaviors, and that an understanding of these dynamical phenomena will serve to connect disparate areas of clinical inquiry. We hope the model that we have outlined in this paper offers one step in that direction.

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