Title
A Nonlinear Dynamical Systems Approach to Emotional Attractor States during Media Viewing

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 43(43)

ISSN
1069-7977

Authors
Han, Jingjing
Amon, Mary Jean

Publication Date
2021

Peer reviewed

A Nonlinear Dynamical Systems Approach to Emotional Arousal Attractor States during Media Viewing

Jingjing Han (hanjing@alumni.iu.edu)
School of Journalism, Fudan University
Institute for Global Communications and Integrated Media, Fudan University
400 Guoding Road, Shanghai, 200433, China

Mary Jean Amon (mamon@ist.ucf.edu)
School of Modeling, Simulation and Training, University of Central Florida
3100 Technology Parkway, Orlando, FL 32826

Abstract

This study examined dynamic attractor states in skin conductance activity during resting baselines and media viewing in order to determine if there are qualitatively distinct dynamics during information processing and whether those dynamics vary based on features of task stimuli. The results indicate that media viewing shifts one from a resting non-chaotic attractor to a chaotic attractor. Content valence (positive or negative) and the emotional context in which videos were delivered (presentation order) had significant impact on the probability of exhibiting a chaotic attractor. Using the nonlinear dynamic systems approach, this study provides novel understandings of emotional information processing, the electrodermal system, and the relationship between physiological and emotional experiences.

Keywords: attractor states; emotional arousal; skin conductance; media viewing; nonlinear dynamical systems theory

Introduction

Emotion is often discussed in terms of discrete states, for example, researchers often reference five primary emotions including joy, sadness, fear, anger, and disgust (e.g., Frijda, 1986). Emotion is also recognized as a continuous process that evolves over time such as increasing and decreasing in emotional valence and arousal. More recently, emotion has been increasingly examined as both a dynamic and nonlinear process that exhibit patterns of change over time and qualitative shifts.

Nonlinear dynamical systems theory (NDST) describes systems composed of many components, where multiplicative interactions among components can give rise to both gradual and sudden, qualitative shifts in behavior (Thelen & Smith, 1994; Strogatz, 1994). As an analytical framework, NDST provides a variety of methods for understanding system-level changes that unfold over time. For example, Boker and his colleagues built damped oscillator models to capture intra-individual variability of emotion which successfully represented participants' long-term hedonic changes and emotional fluctuations following conjugal loss (Bisconti et al., 2004; Boker, 2001; Chow et al. 2005). NDST suggests that human emotion might not only be characterized by discrete emotions and continuous changes in emotion over time but also distinct types of dynamics. In other words, recognizing human emotion as dynamic requires us to understand qualitatively different dynamics that underscore human emotions, as well as the contexts that move us from one type of dynamic to another, the relative stability of those dynamics, and their overall dynamic properties.

Qualitatively different dynamics in NDST can be observed from system attractors or patterns in which systems are reliably drawn. More specifically, attractors refer to different types of states that the system will evolve to and stay in unless there are perturbations to the system (Strogatz, 1994). For example, the Rössler system (Rössler, 1976) produces attractors that can consist of an unstable equilibrium point, a linearly stable equilibrium point, a limit cycle, and a chaotic attractor state. Stable attractors are those that the system prefers to stay in and returns to even after a disturbance, whereas unstable attractors are states a system will easily move away from following a perturbation. Limit cycles are those that spiral over time, and chaotic attractors refer to systems with trajectories that are highly sensitive to initial conditions and never return to the exact same points. Depending on the system's properties and parameters, a system may reveal different combinations of the aforementioned attractor types. The left panel picture in Figure 1 presents the Rössler system with two attractors, under a certain combination of parameters (see the Figure 1 note): the red dot represents an unstable equilibrium point and the blue lines stand for a chaotic attractor.

Attractors are useful in describing continuities and discontinuities in dynamic states, where the latter arises when a particular attractor state becomes less preferred or reliable and another becomes more stable and dominant (Howe & Lewis, 2005). Particular events can interfere with otherwise stable dynamics, resulting in transitional events or qualitative shifts in attractor states. Applied to research on emotion, nonlinear dynamic analyses of EEG signals during video viewing suggest more complex dynamics (higher dimensionality) during affective states compared to neutral states (Aftanas et al., 1997). The authors proposed that increased dimensional complexity might be due to emotional arousal that shifts brain activity toward different dynamic states. Similarly, research shows decreased dimensional complexity in EEG signals during meditation as compared to baselines, where meditation was presumed to 'turn off' networks relevant to internalized attention and inhibition of information processing (Aftanas & Golocheikine, 2002). Thus, EEG research highlights higher-dimensional states during more emotionally arousing and less restful activities. However, research has not determined if the higher-dimensional states suggest a qualitative shift in the attractor state of brain dynamics. Moreover, our general understanding of emotional attractor states is limited. Questions remain in terms of whether there are qualitatively different dynamics during information processing and how those dynamics could be altered as a function of different aspects of stimuli (e.g., positive and negative; calm and arousing; fast and slow emotional change, etc.).

This paper applies methods from NDST to identify dynamic attractor states in emotional arousal during video viewing. We propose that emotional arousal exhibits properties of the Rössler system that consists of two types of attractors: a non-chaotic attractor (e.g., equilibrium points or limit cycle) and a chaotic attractor. Moreover, we propose that attractor indices are not significantly associated with traditional metrics of arousal derived from EDA (e.g., average, average change, etc.), which would suggest attractor metrics have the potential to provide new fruitful directions for understanding EDA response. This study is based on the secondary analysis of data collected from a large research project examining emotional responsivity to different media viewing conditions (Han, 2020). The data used in this study was from an experimental design with 2 (message valence: positive and negative) × 2 (message arousal: calm and arousing) × 2 (message repetition) × 2 (stimulus presentation order: slow and fast) mixed-factor design. Order was a between-subject factor that half of the participants watched one stimulus presentation order with a slow change of emotional valence and arousal from one video to another while the other half of participants watched the other stimulus presentation order with a faster change of emotional valence and arousal between videos. The specific video presentation orders for the slow and fast emotional change conditions can be found on our OSF Online Supplementary Table 1. All other message factors were within-subject factors.

Non-chaotic and chaotic attractors are commonly identified using one of the three methods in physiological systems (Aftanas et al., 1997; Stam et al., 2005). The three methods include identifying signal dimensionality, Lyapunov exponent, and entropy. We used a phase space reconstruction method and calculated dimensionality of each time series across each video viewing for attractor identification. This exploratory study investigated if the probability of exhibiting non- and chaotic attractors of emotional arousal varied as a function of emotional valence and arousal states. Specifically, we compared the attractor type between (1) resting and affective states, (2) negative and positive states, and (3) arousing and calm states. We also examined (4) if stimulus presentation order influenced the attractor type of emotional arousal.

In this regard, we expected that greater emotional arousal would be associated with a chaotic attractor (a higher dimensionality state than the non-chaotic attractor) during video viewing than during baselines (**hypothesis 1**), during arousing video viewing than calm video viewing **(hypothesis 2**), and during the baseline after all video viewing than the baseline prior to all video viewing (**hypothesis 3**). We also expected that the order variable will interact with the baseline effect such that the fast compared to slow change order will more likely lead to chaotic attractors for post-viewing baselines (**hypothesis 4**). Finally, we investigated whether positive video viewing would correspond to chaotic attractors, as compared to negative video viewing (**exploratory research question**).

Method

Stimuli

We used National Collegiate Athletic Association (NCAA) men's basketball games as experimental stimuli. Positive videos were those with the home university leading and negative videos were those with the home university trailing. Games with 1-4 score difference were perceived as arousing and games with 15-25 score difference were perceived as calm. Each video was 3 minute 40 seconds long. In order to assure the successful manipulation of the message valence and arousal variables, team identity and self-reported positivity, negativity, and arousal were measured following each game. Results from those who participated the study show that arousing messages (M = 6.66, SE = .22) were rated significantly more arousing than calm messages (M = 3.64, SE = .20), F (1, 44) = 186.38, p = .000 < .001, partial η^2 = .81. Positive messages ($M_{\text{positivity}}$ = 6.59, SE = .17; $M_{\text{negativity}}$ = 1.79, SE = .15) were rated significantly more positive and less negative than negative messages ($M_{\text{positivity}}$ = 3.33, SE = .19; $M_{\text{negativity}}$ = 5.29, SE = .25), $F_{\text{positivity}}$ (1, 44) = 151.77, p = .000 < .001, partial η^2 = .78; $F_{\text{negativity}}$ (1, 44) = 133.92, p = .000 < .001, partial η^2 = .75.

Participants and Procedures

All procedures were approved by the institution's Internal Review Board. Forty-six students were recruited from the university's communication and psychology department pools, with course credits or a $10 Amazon gift card as their compensation for participation. One participant was an outlier in not supporting the home university during the game viewing; hence this participant's data were deleted from future analyses. Among the final 45 participants (M age = 19.05, SD = .99), most identified as women (n = 31) and White (n = 35, followed by Asians [n = 5], American Indian or Alaska Native [n = 1], and no data for the rest four participants [n =3 did not report and n = 1 was missing due to equipment failure]).

After participants signed the consent form, they were seated in front of a Sony 43-inch Ultra HD television, then researchers began the procedures for physiological data collection. Once physiological signals were ready to be measured, participants were given a brief oral instruction and watched the games in the randomly assigned order. After each game clip, they were asked to rate how positive, negative, and aroused the game made them feel, and which team they rooted for. Two two-minute silent physiological baselines were measured, one before and one after they watched the eight game video clips.

Skin Conductance Activity

Skin conductance activity is a reliable measure of emotional arousal (Dawson et al., 2007). We measured EDA using two EDA electrodes that measured sympathetic nervous system reactivation through the activity of eccrine sweat glands. EDA data were recorded at a 2000Hz sampling rate using a BIOPAC MP150 system (BIOPAC Systems Inc., Santa Barbara, CA). The EDA electrodes were placed on the inner side of participants' left feet, which were connected to EDA wires. Data were cleaned in the Acqknowledge 5.0 software. Because skin conductance data is a slow response signal, data were averaged to 1Hz for analysis.

Post-viewing Emotional Ratings

Emotional ratings were measured on nine-point Likert Scales. Arousal rating ranges from *1* (not at all excited/aroused/awake) to *9* (extremely excited/aroused/awake). Positivity rating ranges from *1* (not at all positive/happy/pleased) to *9* (extremely positive/ happy/ pleased). Negativity rating was measured on the 9-point scale ranging from *1* (not at all negative/unhappy/annoyed) to *9* (extremely negative/unhappy/annoyed).

Attractor Measurement

As mentioned earlier, non-chaotic and chaotic attractors of emotional arousal were assessed via phase space reconstruction (Abarbanel, 1996). Time series data was a one-dimensional data reduced from a higher-level dimensional space. For example, a pendulum operates on a two-dimensional space (i.e. velocity and location dimensions) but common descriptions of a pendulum's trajectory are presented in terms of a one-dimensional time series that is a sine or cosine wave. Phase space reconstruction unfolds the one-dimensional time series data and recovers its higher-level dimensional phase space that the data originally operates on, using the embedding theorem (Takens, 1981). Detailed explanations and specific steps entailed in this method can be found in the supplemental document of our OSF page. A MATLAB program created by Kay and Richardson (2005) was used for parameter setting and dimensionality calculation. Based on the structure of the data, the method estimates the number of dimensions (i.e., the *n*-dimensional phase space) in which the data operates. Because dimensionality larger than two is considered as a chaotic attractor (Abarbanel, 1996; Strogatz, 1994), time series data with dimensionality equal or smaller than two was coded as non-chaotic (with zero indicating an equilibrium point and one indicating a limit cycle, Stam et al., 2005); dimensionality larger than two was coded as chaotic.

The time series data from each video were processed and passed to the MATLAB program. The program then produced one numerical value indicating its dimensionality, which was used to determine whether it is a chaotic or non-chaotic attractor. This resulted in eight binary values (one for each video) for the attractor variable for each participant.

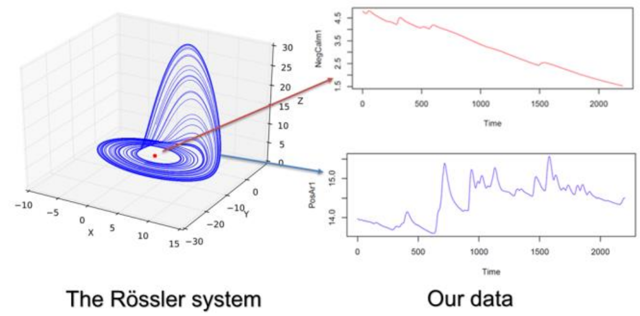

Figure 1. The red line on the top right panel is illustrated as a red non-chaotic (fixed-point) attractor—unfolded over time—in the left three-dimensional space. The blue time series data on the bottom right panel unfolds as a higher-dimensional blue chaotic attractor in the left panel. The left panel figure is adapted from Wikipedia, and a similar graph can be replicated by using the Rössler Attractor Simulink Model, Moysis, 2016 (see differential equations in Rössler, 1976).

Data Analyses

Model 1. A binary logistic regression model was built to test hypotheses 1, 3, and 4 and the exploratory research question with video valence, order, and their interaction as predictors and the attractor type (chaotic [1] or non-chaotic [0]) as the outcome variable. Valence had four levels so as to test multiple hypotheses in one model: positive video, negative video, and two levels of residual valence including pre-viewing baseline and post-viewing baseline. Order had two levels including slow and fast emotional change rates. Contrasts were specified in the model to compare baselines (two levels combined) versus stimulus (negative and positive video viewing segments combined) for hypothesis 1, pre-viewing to post-viewing baselines for hypothesis 3 and 4, and positive video viewing to negative video viewing for research question 1.

The Hosmer-Lemeshow test was not significant ($\chi^2(4)$ = .00, p = 1.00) suggesting the model was correctly specified. The model's -2Log likelihood = 395.76, and the Nagelkerke R^2 = .21.

Model 2. Model 2 replaced the variable video valence with video arousal to test if arousing videos produced a more chaotic attractor than calm videos (hypothesis 2). All other parameters were identical to Model 1. Like Model 1, Model 2 was correctly specified. The Hosmer-Lemeshow test was not significant ($\chi^2(4)$ = .00, p = 1.00), the model's -2Log likelihood = 409.55, and the Nagelkerke R^2 = .17.

Results

Association between Attractors and Traditional Measures of Arousal

We first correlated Attractor with other traditional skin conductance measures. Point biserial and Pearson correlations were used to correlate categorical-continuous variables and two continuous variables, respectively. We correlated *Attractor* with *Dimensionality* (the numerical value calculated from the phase space reconstruction method), averaged skin conductance level across each video viewing (*SCL_Mean*) and its standard deviation (*SCL_std*), averaged skin conductance's change score from the video onset (*Change_Mean* = average ($SCL_{time(i)} - SCL_{time0}$)) and its standard deviation (Change_std), and three emotional ratings after each video viewing: arousal rating (Arousal), positivity rating (Positivity), and negativity rating (Negativity).

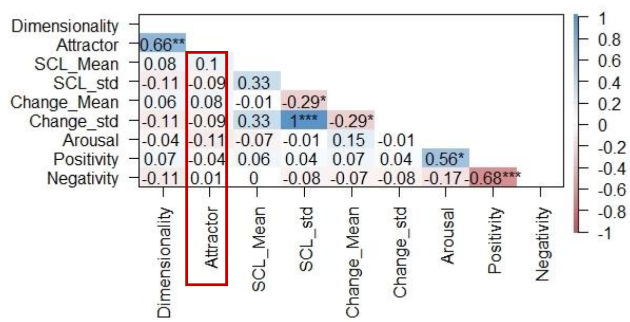

Figure 2: Correlation plot of Dimensionality, Attractor, SCL_Mean, SCL_std, Change_Mean, Change_std, Arousal, Positivity, and Negativity.

The second column of Figure 2 suggests that the correlation sizes of Attractor with more traditional EDA metrics were small and none were significant, p > .05. This was also true of the dimensionality index, which was not significantly correlated with traditional EDA metrics, p > .05. The findings suggest the attractor and dimensionality variables capture distinctive properties of skin conductance data compared to traditional measures.

Hypothesis Testing

In line with hypothesis 1 that video viewing would be associated with more chaotic attractors compared to pre- and post-viewing baselines, Model 1 revealed a main effect of the baseline-versus-stimulus comparison, Wald $\chi^2(1, 3)$ = 26.90, p < .001. Media viewing compared to the two silent baselines increased the probability of the chaotic attractor (B = 4.27, SE = .82, *Odds Ratio* = 71.36, 95% *CI* [14.22, 357.99]). Hypothesis 1 was supported.

Results showed no significant main effect of pre-viewing versus post-viewing baseline, Wald $\chi^2(1, 3)$ = .90, p = .34. However there was a significant interaction effect with Order, Wald $\chi^2(1, 3)$ = 4.93, p = .03 < .05 (B = 1.96, SE = .88, *Odds Ratio* = 7.07, 95% *CI* [1.26, 39.73]). As expected, order had no effect on the probability of chaotic attractor for the pre-viewing baseline, nevertheless it had significant effect on post-viewing baseline. Contrary to our prediction, the slow order led to higher not lower probability of exhibiting the chaotic attractor than the fast order, Wald $\chi^2(1)$ = 5.10, p = .02. On the other hand, from the pre-viewing baseline to the post-viewing baseline, the probability of exhibiting the chaotic attractor increased for the slow changing order (Wald $\chi^2(1)$ = 5.80, p = .02) while it remained the same for the fast changing order (Wald $\chi^2(1)$ = .92, p = .34). Hypothesis 3 was partially supported and Hypothesis 4 was not supported.

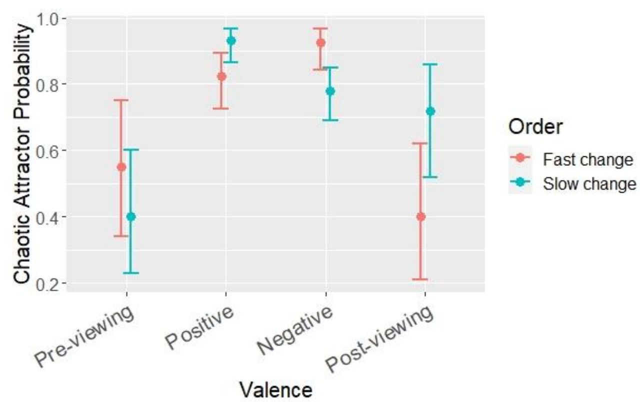

Figure 3: The predicted probabilities (with 95% Wald CI bars) of chaotic attractor in different media viewing contexts.

For research question 1, Model 1 showed that the effect of negative-versus-positive video viewing comparison on chaotic attractor significantly interacted with Order, Wald $\chi^2(1, 3)$ = 11.43, p = .001 < .01 (B = -2.33, SE = .69, *Odds Ratio* = .10, 95% *CI* [.03, .38]). The valence shift from positive video viewing to negative video viewing decreased the probability of exhibiting a chaotic attractor for the slow changing order, but increased for the fast changing order, as shown in Figure 3.

Model 2 revealed no significant effect of video arousal level (calm versus arousing) on chaotic attractor, Wald $\chi^2(1, 3)$ = .23, p = .63 (B = .23, SE = .48, *Odds Ratio* = 1.29, 95% *CI* [.49, 3.22]). Therefore hypothesis 2 was not supported.

Predictability of Emotional Arousal Attractor

We also used regression models to identify the extent to which non-chaotic and chaotic attractors predicted post-viewing self-reported arousal ratings. Specifically, we examined results from a linear multiple regression model with arousal ratings as the outcome variable and the attractor binary data, the average level of skin conductance change from the video onset, and its standard deviation as the predictors. The latter two predictors were included as covariates to examine the predictive value of attractor type over-and-above two traditional EDA metrics.

Results demonstrated that—while the average change in skin conductance was associated with arousal rating (estimated beta = .016, p = .002)—the attractor variable remained predictive for arousal ratings (estimated beta = -.36, p = .02). The finding that both variables predicted self-reported arousal suggests that a chaotic attractor of skin conductance is more likely to lead to lower arousal ratings. Additionally, the standard deviation of skin conductance change score had no predictability on the arousal ratings. Adding the variable of attractor to the model (with skin conductance change score and its standard deviation as predictors) increased the adjusted R^2 from .019 to .032.

Discussion

This study demonstrates distinct dynamics of emotional arousal in different media viewing contexts. Results revealed that media viewing shifts one from a non-chaotic attractor to a chaotic attractor. This shift might be necessary as a chaotic attractor means more flexibility in information processing, where dynamic fluctuations allow participants to more easily respond to different information processing demands in the environment by shifting to different modes from similar baseline states (Aftanas et al., 1997).

We also found that using the slow rather than the fast changing video order led viewers to maintain the attractor mode (i.e., in a chaotic attractor) after watching the videos. Although this result is contrary to our initial prediction, it is in line with previous research on human emotion. Pettersson and colleagues (2013) used an NDST approach and modeled daily variation of human emotions. They found that the further one gets from their equilibrium point, the faster one returns to that point. In other words, fast-changing and intense switches in emotional experiences can lead to faster recovery and return to a more "normal" equilibrium point. In our study, the fast-changing order may have perturbed emotion more intensely than the slow changing order, suggesting that the fast changing order might make one get further away from their initial baselines. This might be the reason that we see its faster recovery during the post-viewing baseline, as compared to the slow changing order for the post-viewing baseline.

This study also found that both content valence and viewing context (i.e., presentation order) predicted the presence of the EDA-based non-chaotic or chaotic attractor states. This suggests that the attractor states reflected by the physiological signal might not have a one-to-one mapping relation with emotional states. This echoes with Boyatzis and colleagues' theorization of two affective attractors in personal and shared vision for management and organizational practice: the positive emotional attractor (PEA) and the negative emotional attractor (NEA). They argued that both of the attractors are strange chaotic attractors and instead of having a one-to-one mapping relation with a single emotional state, or physiological or neurological state, each attractor is characterized by three dimensions including positive or negative emotional arousal, hormonal arousal, and neurological activation. For example, creating a personal or shared vision requires one to be in the PEA that is characterized with positive emotional arousal, endocrine arousal from the parasympathetic nervous systems activation, and neurological activation of the default mode network as opposed to the task positive network (Boyatzis et al., 2015). Future analyses of this present study could explore if the occurrence of chaotic attractor is moderated by viewer attentiveness toward the videos. Testing the relationship between attention and probability of emotional arousal attractor might increase our understanding of the valence by order interaction pattern in predicting attractor state.

The arousing level had no effect on the attractor type. Earlier research suggests that arousing moments elicit skin conductance responses (SCRs, spikes in Figure 1, Potter & Bolls, 2012), leading to possible higher probability of exhibiting a chaotic attractor. Nevertheless, this study showed that calm videos produced the same probability of a chaotic attractor as arousing videos. We suspect that this may be due to the nature of the stimuli we used in this study. For NCAA basketball games, scoring and winning moments might be more important for basketball fans than if the game is close (arousing) or lopsided (calm). Therefore, scoring moments might be more likely to elicit SCRs, making content valence a more influential variable affecting the type of attractor than content arousal. This might speak to the significant finding for the valence effect but not the arousal effect on attractor. Future research should use different genres (e.g., TV shows and commercials) and see if the results in this study are replicated.

This study contributes to broader understandings of the EDA system. First, it provides a possible underlying mechanism for non-specific skin conductance responses (NS-SCRs). NS-SCRs occur regularly without external stimulation, and therefore they are also called spontaneous SCRs. Healthy adults on average have five NS-SCRs per minute and the number can reach to ten for some people (Zimmer, 2000). Previous research shows that one's NS-SCR rate is relatively stable over time and thus is interpreted as a trait called "electrodermal lability" (Crider, 1993). Those with a high frequency of NS-SCRs are called labiles and those with few NS-SCRs are stabiles (Dawson et al., 2007). This study suggests that those non-stimulus-evoked SCRs might derive from the nature of the system's chaotic attractor as the system operates on such an attractor that generates SCRs regularly. Our findings lend support for the notion that the EDA system for people categorized as labiles is operating on a chaotic attractor while the EDA system for stabiles might be on a non-chaotic or less chaotic attractor. Research shows that EDA lability reflects the ability of information processing. As labiles are more vigilant and usually outperform stabiles on various information processing tasks, future research could test, as mentioned earlier, if the chaotic attractor is associated with attention, recall, or additional factors associated with emotional sensitivity. Thus, our findings of distinct attractor states (non-chaotic and chaotic attractors) may complement those on individual differences associated with EDA lability.

Second, this study found an important predictor for arousal rating. For decades, physiologists and emotion scientists have no clear explanations on the difference between physiological and emotional experiences. The only thing that the previous research is consistent on is that the two are always different or sometimes even conflict with each other. The regression models suggest that the SCL change score explains only 1.9% of the variances of arousal ratings. Once we added the attractor variable to the model, the skin conductance activity (including the change score and the attractor variable) overall accounts for up to 3.2% of the rating variance. Consistent with prior theoretical work calling for a dynamic computational architecture for understanding emotion as an emergent process (Scherer, 2009), this finding suggests that dynamics of skin conductance is a significant factor influencing one's emotional experiences. Future research may follow-up on this finding by searching for additional dynamic properties of physiology that might affect and predict emotional experiences.

Future research could use additional types of nonlinear dynamical analyses to increase our understanding of the distinct features of the emotional arousal attractors. For example, fractal analysis can be used to examine if the chaotic attractor has significantly different fractal dimensions as a function of message valence, arousal, and emotional change rate. Recurrence analysis can also be used to compare the size of attractor between different media viewing conditions.

Conclusions

Overall, our preliminary study reveals an important feature of the EDA system that has previously garnered little attention from physiologists and emotion scientists, with few exceptions (e.g., Scherer, 2009). Our findings suggest that the distinction between EDA-based attractor states may represent an important marker for information processing research as it (1) differentiates resting and affective states and positive and negative states; and (2) is sensitive to context change during information processing. Critically, the attractor indices were not significantly correlated with more traditional EDA metrics and significantly improved models predicting self-reported emotional experience over-and-above traditional metrics, demonstrating its unique potential for understanding emotional states. In addition, this notion of emotional attractor states might also contribute to our understanding of human physiology more generally. As previously noted, attractor states have the potential to further understanding of EDA lability and individual differences in the EDA system, as well as the relationship between physiological and emotional experiences.

Acknowledgments

This work was supported by the Institute for Communication Research at the Media School of Indiana University Bloomington.

References

Abarbanel, H.D.I. (1996). *Analysis of observed chaotic data*. Springer.

Aftanas, L. I., & Golocheikine, S. A. (2002). Non-linear dynamic complexity of the human EEG during meditation. *Neuroscience letters*, *330*(2), 143-146. doi:10.1016/s0304-3940(02)00745-0

Aftanas, L. I., Lotova, N. V., Koshkarov, V. I., Pokrovskaja, V. L., Popov, S. A., & Makhnev, V. P. (1997). Non-linear analysis of emotion EEG: Calculation of Kolmogorov entropy and the principal Lyapunov exponent. *Neuroscience letters*, *226*(1), 13-16. doi: 10.1016/s0304-3940(97)00232-2

Bisconti, T. L., Bergeman, C. S., & Boker, S. M. (2004). Emotional well-being in recently bereaved widows: A dynamical systems approach. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *59*(4), 158-167. doi:10.1093/geronb/59.4.p158

Boker, S. M. (2001). Differential models and "differential structural equation modeling of intraindividual variability" In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change*. American Psychological Association.

Boyatzis, R. E., Rochford, K., & Taylor, S. N. (2015). The role of the positive emotional attractor in vision and shared vision: toward effective leadership, relationships, and engagement. *Frontiers in Psychology*, *6*, 670.

Chow, S.-M., Ram, N., Boker, S. M., Fujita, F., & Clore, G. (2005). Emotion as a Thermostat: Representing Emotion Regulation Using a Damped Oscillator Model. *Emotion*, *5*(2), 208–225. doi:10.1037/1528-3542.5.2.208

Crider, A. (1993). Electrodermal response lability-stability: Individual difference correlates. In J. C. Roy, W. Boucsein, D. C. Fowles, & J. H. Gruzelier (Eds.), *Progress in Electrodermal Research*. Plenum Press.

Dawson, M. E., Schell, A. M., & Filion, D. L. (2007). The electrodermal system. In John Cacioppo, Louis Tassinary, & Gary Berntson (Eds.), *Handbook of psychophysiology*. Cambridge University Press.

Frijda, N. H. (1986). *The emotions*. Cambridge University Press.

Han, J. (2020). Physiological and Emotional Synchrony during Television Viewing: A Nonlinear Dynamic Systems Approach (Publication No. 28002093) [Doctoral dissertation, Indiana University]. ProQuest Dissertations Publishing.

Howe, M. L., & Lewis, M. D. (2005). The importance of dynamic systems approaches for understanding development. *Developmental Review*, *25*(3-4), 247-251. doi:10.1016/j.dr.2005.09.002

Kay, B. & Richardson, M. J. (2015). Recurrence quantification analysis conducting using MATLAB code for the APA Advanced Institute of Nonlinear methods for Psychology Science. https://github.com/xkiwilabs.

Kondakor, I., Brandeis, D., Wackermann, J., Kochi, K., König, T., Frei, E., Pascual-Margui, R.D., Yagyu T., & Lehmann, D. (1997). Multichannel EEG fields during and without visual input: frequency domain model source locations and dimensional complexities. *Neuroscience Letters*, *226*(1), 49-52. doi:10.1016/s0304-3940(97)00224-3

Pettersson, E., Boker, S. M., Watson, D., Clark, L. A., & Tellegen, A. (2013). Modeling daily variation in the affective circumplex: A dynamical systems approach. *Journal of Research in Personality*, *47*(1), 57-69. doi:10.1016/j.jrp.2012.10.003

Rössler, O. E. (1976). An equation for continuous chaos. *Physics Letters A*, *57*(5), 397-398. doi:10.1016/0375-9601(76)90101-8

Rössler system. (n.d.). In Wikipedia. https://en.wikipedia.org/wiki/R%C3%B6ssler_attractor

Potter, R. F., & Bolls, P. (2012). *Psychophysiological measurement and meaning: Cognitive and emotional processing of media*. Routledge.

Scherer, K. R. (2009). Emotions are emergent processes: They require a dynamic computational architecture. *Philosophical Transactions of the Royal Society B, 364*, 3459-3474. doi:10.1098/rstb.2009.0141

Stam, C. J. (2005). Nonlinear dynamical analysis of EEG and MEG: review of an emerging field. *Clinical neurophysiology*, *116*(10), 2266-2301. doi: 10.1016/j.clinph.2005.06.011

Strogatz, S. H. (1994). *Nonlinear dynamics and chaos: with applications to physics, biology, chemistry, and engineering*. Perseus Books Group.

Moysis, L. (2016). Rossler Attractor Simulink Model (https://www.mathworks.com/matlabcentral/fileexchange/46601-rossler-attractor-simulink-model), MATLAB Central File Exchange.

Takens, F. (1981). Detecting strange attractors in turbulence. *Lecture notes in mathematics*, *898*(1), 366-381.

Thelen, E., & Smith, L. B. (1996). *A dynamic systems approach to the development of cognition and action*. MIT press.

Zimmer, H. (2000). Frequenz und mittlere Amplitude spontaner elektrodermaler Fluktuationen sind keine austauschbaren Indikatoren psychischer Prozesse [Frequency and mean amplitude of spontaneous electrodermal fluctuations do not convey identical information about mental processes]. *Zeitschrift für Experimentelle Psychologie*, *47*(2), 129–143.