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A chaos-based analysis of finger plethysmogram for deception detection: effects of stimulus similarity on concealed information processing

Dihao Wang

Komazawa University, Tokyo, Japan

3084101d@komazawa-u.ac.jp

Abstract. Deception detection remains an important aspect of the forensic, security, and psychological domains. Even though traditional polygraphy relies on multiple physiological measures of deception, the effectiveness of deception detection based on chaos theory measures of pulse waves remains relatively unexplored. Chaos theory measures the inherent complexity of a signal and can potentially reveal patterns in deception detection that might otherwise remain hidden by traditional linear measures of deception detection. This study aimed to explore the effectiveness of fingertip plethysmogram chaos theory measures in deception detection in the context of simulated theft with a 2 x 2 factorial design involving stimulus similarity (high and low) and stimulus type (probe and irrelevant). Largest Lyapunov Exponent (LLE) measures were calculated from 560 experiments conducted on 14 participants. Analysis of variance revealed significant main effects of stimulus type ($F(1,13) = 9.26$, $p = .009$) and the interaction of stimulus similarity and stimulus type ($F(1,13) = 6.93$, $p = .021$). Furthermore, under low similarity conditions, LLE of the probe condition exceeded the irrelevant condition ($t(13) = 4.23$, $p < .001$, $dz = 1.13$). Generalized estimating equations revealed significant effects of LLE on deception detection at the individual trial level ($\beta = 0.575$, $p = .006$). Permutation tests revealed significant effects of LLE on deception detection ($p = .021$). Overall, the results suggest the effectiveness of LLE in deception detection in low similarity conditions and support the effectiveness of chaos theory measures of deception detection with boundary conditions in mind.

Keywords: fluctuation, chaos analysis, deception detection, similarity, Largest Lyapunov Exponent, fingertip plethysmogram

1. Introduction

Deception, as measured through lying, is a ubiquitous characteristic of human social interaction. Although deception is seen to serve a number of important functions in maintaining social relationships and protecting privacy, it is also seen to pose a number of important challenges, especially in forensic, security, and interpersonal contexts. The search for understanding deception detection has been a longstanding one, especially in psychological, neuroscientific, and law enforcement contexts [1]. It has been observed that deception detection is a multi-factorial process that consists of cognitive, affective, and behavioral aspects making the process more complex. The traditional methods of deception detection have still been relying much on observing body, speech and body language. One of them, polygraph testing, has been identified to be the most widely applied technique of deception detection particularly within the forensic setting where it entails measuring a variety of autonomic nervous system reactions primarily breathing, skin conductivity, and heartbeat [2].

This study recognizes that the measures used in traditional polygraphy are generally linear in nature and might not account for the inherent nonlinear processes involved in deception detection. Advances in nonlinear dynamics and chaos theory suggest promising approaches in detecting subtle changes in physiological signals that might have escaped traditional linear measures of deception detection. Chaos theory and the computation of the Largest Lyapunov Exponent (LLE) provide an objective measure of the complexity of the signal and the inherent stability of the system. This might uncover hidden patterns in physiological responses related to concealed information [3]. The fingertip plethysmogram is an easily accessible physiological measure of peripheral blood flow and the autonomic nervous system. Previous studies have found significant correlations between LLE and states of anxiety, fear, and relaxation and might be sensitive to the underlying processes of deception.

This study aims to investigate the feasibility of using chaos analysis of fingertip plethysmogram for deception detection, with particular attention to how stimulus similarity contexts affect the discriminability of probe versus irrelevant stimuli based on LLE values.

2. Literature review

2.1. Deception detection: theory and methods

Deception research emphasizes cognitive load theory, positing that generating false information requires greater executive resources than truthful responding. Theory of mind capabilities enable representation of others' mental states, fundamental for successful deception. Neuroimaging identifies multiple brain regions including prefrontal cortices and anterior insula associated with deceptive responding, suggesting complex executive control and memory manipulation processes. The Concealed Information Test paradigm presents crime-relevant probe items among neutral irrelevant items, capitalizing on differential physiological responses to personally significant information [4]. Event-related potential research demonstrates enhanced P300 amplitudes when encountering concealed probe stimuli, reflecting involuntary orienting responses. However, debate persists regarding response specificity to deception versus confounds including arousal, cognitive effort, and emotional salience [5].

2.2. Physiological indices and autonomic responses

Modern polygraph tests involve various parameters, such as respiratory activity, electrodermal activity, cardiovascular activity, and pulse volume. Skin conductance is also effective in this regard, as it shows high sensitivity to orienting responses to emotionally relevant stimuli. Heart rate shows characteristic deceleration patterns in response to the presentation of probes, suggesting high levels of attention allocation. Electroencephalographic activity, specifically P300 potentials, shows high discrimination between probe and non-relevant stimuli in individuals who are guilty. Despite technological advances, fundamental challenges remain regarding response specificity and individual differences in physiological reactivity. Traditional linear measures may inadequately capture complex autonomic dynamics, motivating investigation of nonlinear analytical approaches [6, 7].

2.3. Chaos analysis and LLE in physiological signals

Chaos theory provides frameworks for understanding complex systems exhibiting deterministic yet apparently random behavior. Biological systems including cardiovascular regulation operate as nonlinear dynamical systems characterized by feedback loops and adaptive complexity. Chaos analysis reconstructs system attractors through phase space embedding, computing measures including Lyapunov exponents quantifying system complexity. The Largest Lyapunov Exponent measures exponential divergence rates between nearby trajectories, indexing system predictability with positive values indicating chaotic dynamics. Application to fingertip plethysmogram enables quantification of peripheral blood flow dynamics reflecting autonomic nervous system activity. Previous research associates LLE with psychological states including anxiety and fear, with higher LLE suggesting greater system flexibility. Studies report adaptive healthy states correspond to elevated LLE reflecting regulatory capacity, whereas reduced LLE may indicate compromised function [8-10].

3. Methods

3.1. Participants and design

Fourteen university students (7 males, 7 females) aged 20-24 years (M = 22.57, SD = 1.51) participated. All were right-handed with normal vision and no physical/psychological conditions interfering with participation. Participants received monetary compensation including 1,000 yen contingent upon successfully concealing information, enhancing ecological validity. The design of the study employed a 2 x 2 within-subjects design with similarity (high/low) and stimulus type (probe/irrelevant) as the independent variables. For the low similarity condition, heterogeneous stimuli (e.g., green pen, ruler, eraser, pencil, nail clipper) were used, whereas homogeneous stimuli (e.g., green pen, red pen, blue pen, yellow pen, black pen) were used in the high similarity condition. The green pen was used as the probe stimulus in all conditions. Each participant completed 40 trials with 10 in each condition and a total of 560 trials.

3.2. Apparatus and procedure

Fingertip plethysmogram signals were acquired using Lyspect 3.5 (Caotech Corporation) with cuff sensors on non-dominant hand fingers. Visual stimuli appeared on a 27-inch monitor 100cm from participants. Sampling rate was 200Hz over 30-second epochs. The mock theft task involved selecting boxes containing green pens, money, and instructions to conceal items while denying possession during testing (see Figure 1 and Figure 2). Each trial presented four images sequentially (5 seconds each) with experimenters posing questions requiring "no" responses. Probe trials contained one probe among three irrelevant images; irrelevant trials contained four irrelevant images. Participants attempted avoiding detection to retain monetary incentives.

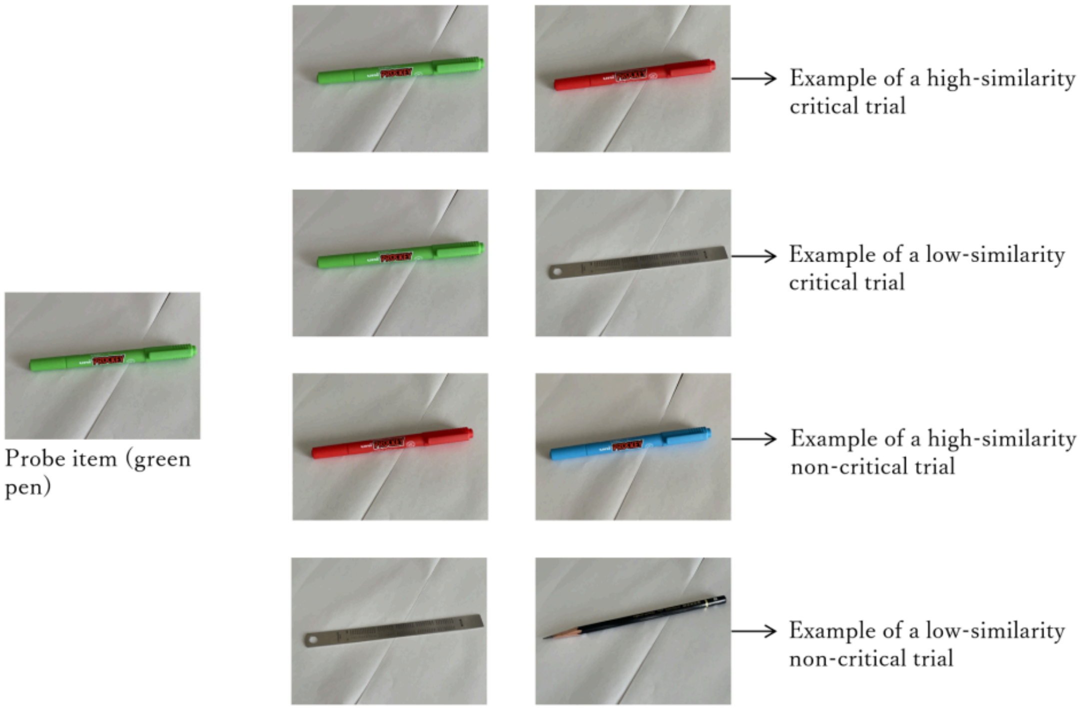

Figure 1. Example trial structure

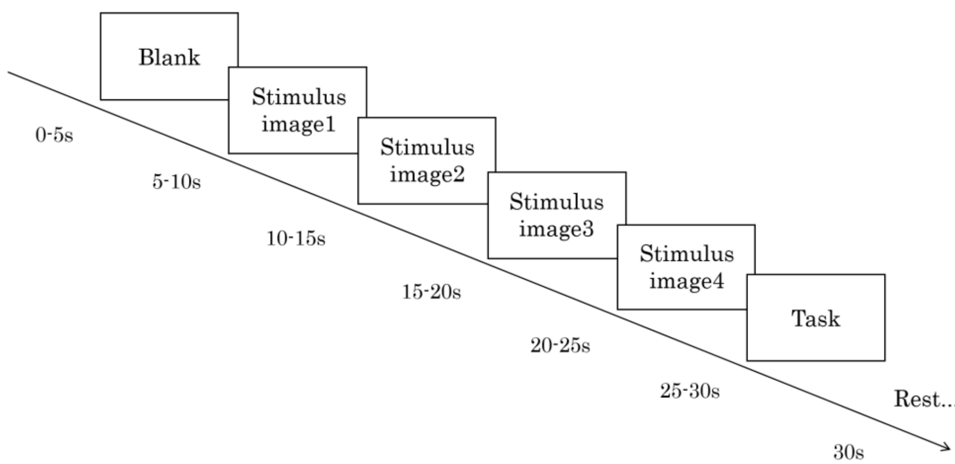

Figure 2. Stimulus presentation sequence

3.3. Data analysis

Plethysmogram data underwent chaos analysis computing Largest Lyapunov Exponent values. Finger plethysmogram time-series data were subjected to chaos analysis, and LLE derived from the finger plethysmogram was used as the dependent variable for all subsequent statistical analyses. The LLE was computed from the reconstructed attractor as a quantitative index of orbit instability, reflecting how strongly trajectories originating from nearby points diverge over time. Statistical inference used participant-level aggregation computing condition means for 2 × 2 repeated-measures ANOVA examining similarity and stimulus type effects plus interaction. Significant interactions prompted simple effects analyses using paired t-tests with Cohen's dz effect sizes. Robustness was further assessed using permutation testing to confirm the significance of the interaction effect without relying on parametric distributional assumptions.

4. Results

4.1. Descriptive statistics

The overall mean LLE was 6.81 for probe conditions and 6.48 for irrelevant conditions, with a difference of 0.33 units. For high similarity conditions, LLE was 6.68 on probe conditions compared with 6.64 on irrelevant conditions, with a difference of 0.04 units. For low similarity conditions, LLE was 6.93 on probe conditions, compared with 6.33 on irrelevant conditions, with a difference of 0.60 units, which was 75% of the pooled standard deviation. For high and low similarity conditions, LLE was 6.66 and 6.63, respectively. Since the unit of inference was the participant, trial-level LLE was aggregated to form four condition means per participant, which was used as input to 2 x 2 repeated-measures ANOVA and paired t-tests. Visual inspection revealed crossover interaction patterns, with differences between probe and irrelevant conditions minimal at high similarity but large at low similarity (see Figure 3).

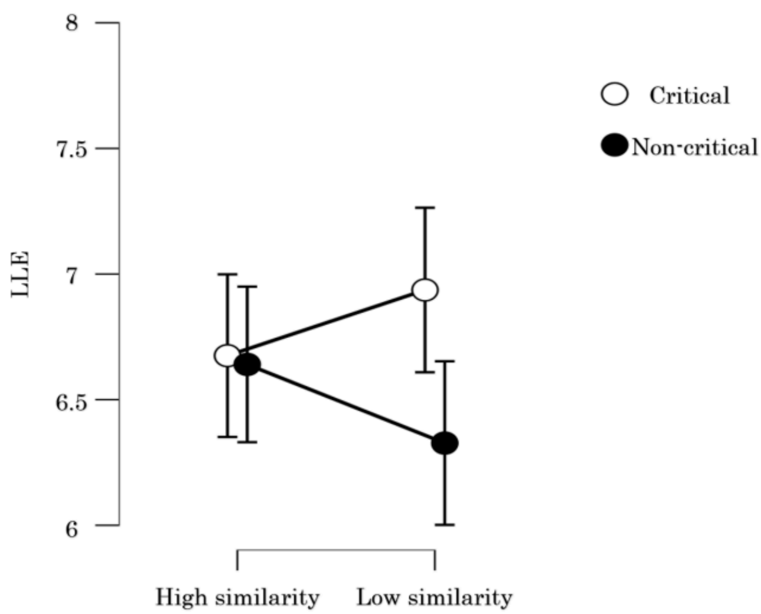

Figure 3. LLE changes by similarity and probe conditions

4.2. Primary ANOVA and simple effects

The repeated-measures ANOVA results did not show a significant main effect of similarity, $F(1,13) = 0.044$, $p = .837$, $\eta_p^2 < .01$. There was, however, a significant main effect of stimulus type, $F(1,13) = 9.262$, $p = .009$, $\eta_p^2 = .416$, with probe stimuli ($M = 6.81$) showing higher LLE than irrelevant stimuli ($M = 6.48$). More importantly, there was also a significant. Simple effects analysis within high-similarity conditions showed no significant probe-irrelevant difference, $t(13) = 0.218$, $p = .831$, $dz = 0.058$. Within low-similarity conditions, probe stimuli ($M = 6.93$) produced significantly higher LLE than irrelevant stimuli ($M = 6.33$), $t(13) = 4.228$,

$p < .001$, $dz = 1.130$, with large effect size exceeding one standard deviation, indicating robust differentiation when stimuli varied substantially in appearance and category (see Figure 4 and Figure 5).

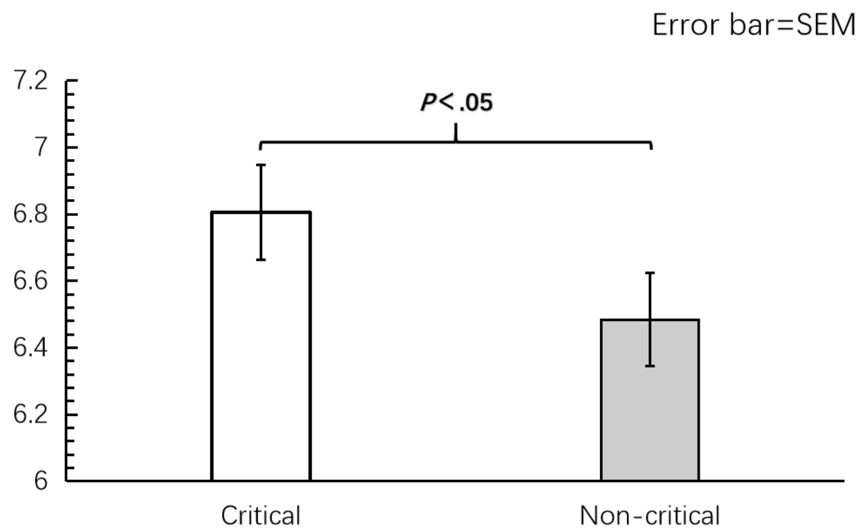

Figure 4. LLE differences between probe and irrelevant conditions

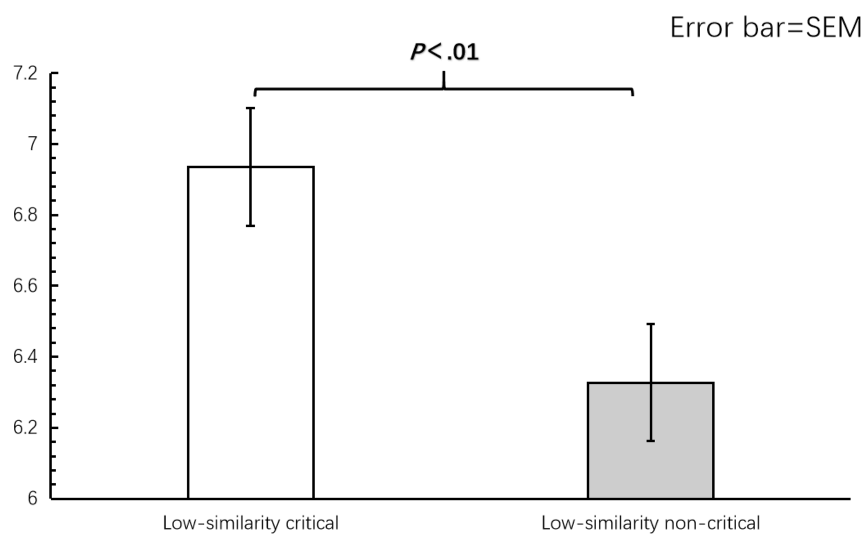

Figure 5. LLE differences in low-similarity probe versus irrelevant conditions

4.3. Robustness verification

Permutation testing on participant-level interaction contrasts yielded $p = .021$, matching parametric ANOVA results and confirming interaction significance through distribution-free inference. At the trial level, Generalized Estimating Equation (GEE) analysis also supported a significant similarity × stimulus type interaction ($\beta = 0.575$, $p = .006$), corroborating the participant-level inference. Trial sequence covariate was non-significant, $\beta = -0.0002$, $p = .566$, indicating no systematic habituation or fatigue trends. Convergence across parametric ANOVA, permutation, and GEE approaches provided robust triangulated evidence supporting reliable stimulus similarity moderation of concealed information detectability through chaos-based plethysmogram indices.

5. Discussion

5.1. Main findings and theoretical implications

This investigation demonstrated fingertip plethysmogram chaos analysis feasibility for deception detection while revealing critical contextual boundary conditions. The significant stimulus type main effect provides direct evidence that physiological signal complexity captured through chaos metrics differentiates concealed versus non-concealed information, aligning with research suggesting deception-associated cognitive-emotional processes increase autonomic arousal manifesting as elevated LLE. Most critically, the robust similarity × stimulus type interaction revealed probe detectability through LLE varied dramatically across contexts. High-similarity scenarios where probe items were perceptually and semantically similar to irrelevant items showed virtually identical LLE responses, indicating chaos metric failure discriminating concealed information when items were highly confusable. Conversely, low-similarity conditions demonstrated effective detection with markedly elevated probe LLE relative to irrelevant stimuli.

5.2. Mechanisms and comparison with prior research

Several mechanisms may explain these findings. First, probe distinctiveness in low-similarity contexts may enhance involuntary orienting and cognitive conflict when denying recognition of obviously different stimuli, thereby increasing autonomic activation captured by LLE. Second, high similarity may impose greater cognitive load even for irrelevant items, potentially elevating baseline complexity and reducing differential responding. These findings parallel Concealed Information Test research documenting that probe-irrelevant discrimination depends critically on stimulus distinctiveness. Changes in LLE can be interpreted as reflecting an integrated response of the brain and the nervous system, and the present findings suggest that contextual factors such as similarity may modulate the detectability of concealed information through chaos-derived indices.

6. Conclusion

This study established chaos analysis of fingertip plethysmogram as viable for deception detection. The Largest Lyapunov Exponent successfully differentiated probe from irrelevant stimuli under low-similarity conditions, exhibiting large statistically robust differences. Conversely, high-similarity conditions showed negligible differentiation, suggesting detection failure when contextual distinctiveness was reduced. Results highlight that successful implementation requires careful stimulus construction ensuring perceptual and semantic differentiation between probe and comparison items. Convergence of repeated-measures ANOVA, permutation testing, and trial-level GEE modeling provides robust evidence. Future research should examine chaos indices combined with traditional measures, explore high-stakes scenarios, and develop integrated multimodal approaches. This research demonstrates proof-of-concept for chaos analysis as a novel deception detection modality while advancing understanding of how contextual similarity shapes responses to concealed information.

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