Complexity Matching in Dyadic Interaction

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Conversation is a complex coordination of human behaviours (Riley, Richardson, Shockley, & Ramenzoni, 2011). Recent theoretical discussion of dyadic coordination has focused on issues of synchronization, entrainment, alignment, and convergence. All of these terms refer to a local matching of specific behavioural and linguistic events, such that members of a dyad coordinate by "doing the same thing." Though much research has studied dyadic coordination that goes beyond mere synchrony, few studies have analysed dynamics beyond synchrony and phase. Communicative behaviours tend to be highly variable, irregular, and heterogeneous, like most human behaviours. Therefore, it appears that there could be more complex temporal patterns, beyond local matching and into the management of more complex dynamics of interaction.

More complex patterns are often expressed by *heavy-tailed distributions* (i.e., heavier than an exponential fall off) that reflect variations across wide ranges of timescales. For instance, long-run variations in the acoustics of speech signals are known to follow a pattern of so-called "*1/f* noise"—irregular fluctuations in amplitude occur across a wide range of frequencies yet fall into a power law relationship with each other (Voss & Clark, 1978).

The term *complexity matching* was recently coined by West and colleagues to refer to the concept that interacting complex systems may become coordinated in a way that is reflected in distributional and temporal measures of their complexity (West, Geneston, & Grigolini, 2008). In particular, the statistical shapes of their complexities should have a tendency to match up. This tendency is hypothesized to be adaptive because models exhibit maximal information transmission between them when the complexities of their activities match up.

In the present study, we tested whether complexity matching can be detected between conversational partners and if different conversational contexts constrain the dynamics differentially.

Method

Twenty-eight undergraduate students from the University of California, Merced were instructed to freely discuss topics in one ten-minute argumentative conversation and one ten-minute affiliative conversation with another student. Experimenters determined the topic of argument by comparing survey answers participants had previously completed to identify the topic on which participants held strong but opposing views. Participants were instructed to convince one another of their opinion. For the affiliative conversation, dyads were instructed to discuss popular media both participants enjoyed. Conversation prompts were counterbalanced across the dyads. Conversations were captured on a Canon Vixia HF M31 HD Camcorder, mounted on a Sunpak PlatinumPlus 600PG tripod. Audio signals were simultaneously digitally recorded at 44 kHz (Paxton & Dale, under review).

Fifty-six audio files were recorded (four per dyad, two per participant) and imported into Audacity for removal of spurious noise artifacts (e.g., noise, cross-talk from other subject's acoustic signal), identifying sound (intensity above -30db), and generating onset/offset intervals marked as acoustic speech events - resulting in four event time series per dyad – two per conversation, one for each partner.

Results and Discussion

To extract both distributional and temporal complexities from a single measure of acoustic speech signals, series of inter-event intervals (IEIs) were computed for the former and a series of binary spike trains of speech events were computed for the latter.

Distributional Analyses. *Multi-model inference* (MMI; Burnham & Anderson, 2002) was used to test for heavy tails in IEI distributions. MMI results showed that the lognormal function was most likely to generate the observed IEI distributions (n=56 individual distributions, 100% lognormal). Lognormal distributions can be thought of as constrained, or sometimes truncated, power law distributions and can be characterized by a mean (μ) and standard deviation (σ) under logarithm transformation. Because of the transform, σ roughly corresponds to the heaviness of the tail.

The σ's for affiliative (σ_{mean} = 1.48, SE = .03) and argumentative (σ_{mean} = 1.54, SE = .03) conversations were significantly different from each other, $t(27)$ = -3.03, p = .005. Observing differences in σ across different conversation contexts provides evidence that this measure of complexity in IEI distributions is sensitive to conversation type, rather than just low-level acoustic and articulatory effects.

Temporal Analyses. To estimate the properties of temporal complexity (e.g., 1/f noise) in speech event time series (see Figure 1a/b), we implemented the Allan Factor (AF) analysis (Allan, 1966). For AF, each time series is tiled with adjacent windows of size T, and the number of events N_j is counted within each window j. The differences in counts between adjacent windows is computed as $d(T) = N_{j+1}(T) - N_j(T)$, and d(T) series are computed across the range of possible values of T given the length of the time series, where T is varied as a power of two. The Allan factor for a given timescale T is the expected value of the squared differences, normalized by mean counts of events per window,

$$A(T) = \frac{\langle d(T)^2 \rangle}{2\langle N(T) \rangle}.$$

Poisson processes yield $A(T) \sim 1$ for all T, whereas power law clustering yields $A(T) \sim (T/T_1)^{\alpha}$, where T_1 is the smallest time scale considered, and α the exponent of the scaling relation. Point processes with $\alpha \sim 0$ are Poisson-distributed, meaning that events occur at random, independent points in time. By contrast, point processes with α near the upper bound of $\alpha \sim 1$ exhibit clustering that follows a power law distribution across timescales and can be considered fractal stochastic point processes (Lowen & Teich, 2005).

For the AF analysis, α's for affiliative (α_{mean} = .44, *SE* = .02) and argumentative (α_{mean} = .55, *SE* = .03) conversations were significantly different from each other, $t(27) = 4.70$, $p < .001$ (see Figure 1c).

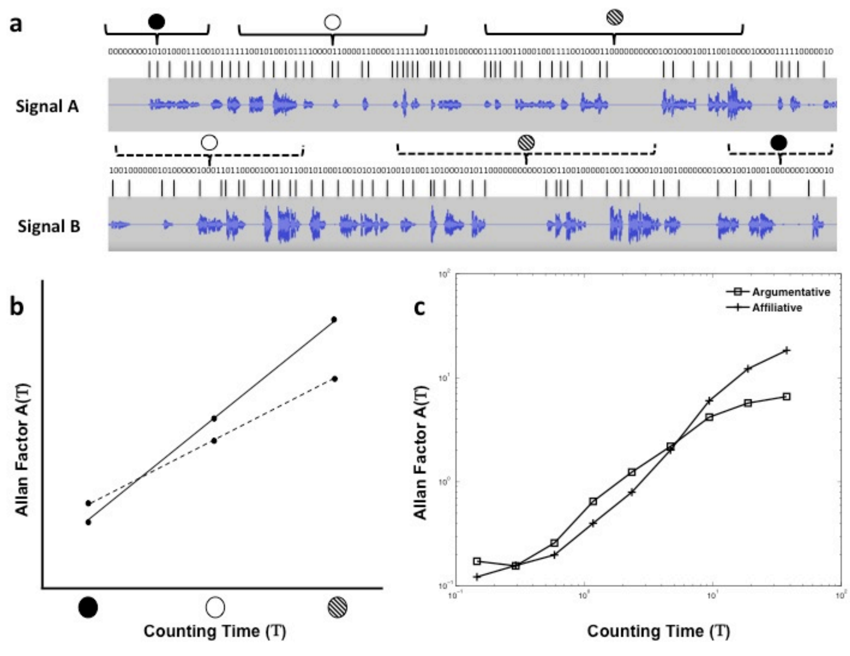

Figure 1. (a) .wav file to speech event point process to binary spike train. (b) Idealized plot of Allan Factor estimates for each window size, *T*. Note the differences in slope between Signal A and Signal B from 1a. (c) Aggregated Allan Factor functions by conversation type.

Complexity Matching by Conversation Type. To test for complexity matching between interlocutors, we compared differences of AF functions across conversations types. Each acoustic signal's estimated AF function was comprised of nine timescales. To compare two AF functions for a given dyad, we took the absolute difference of the two interlocutors' AF estimate for each of the nine timescales, and summed them to create an AF difference function value for each dyad in each conversation. AF difference function sums closer to 0 indicates more matching. The average sums of the AF differences for affiliative (M = 21.21, SE = 4.35) and argumentative (M = 40.38, SE = 6.43) conversations were significantly different from each other, $t(13) = 4.25$, $p = .001$.

General Discussion. Analyses of conversational data from Paxton and Dale (under review) indicated that acoustic speech events in dyadic interactions show properties of heavy-tailed distributions and power law clustering. Distributional and temporal measure of complexity, σ of the lognormal and the AF function, respectively, were observed and found to differ as a function of conversation type. These differences indicated that the measures of complexity reflected aspects of conversation beyond low-level articulatory and acoustic effects. Furthermore, more complexity matching was observed in affiliative conversations relative to argumentative conversations. Complexity matching between interlocutor's speech events was constrained by conversational context.

The original formulation of complexity matching (West, Geneston, & Grigolini, 2008) suggests that a consequence of complexity matching is optimal information transmission. Future research in complexity matching of dyadic interaction should incorporate measures of performance that might suggest such optimality of information transmission and comprehension among interlocutors.

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