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Texting and Tapping: A Dynamical Approach to Multitasking

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Abstract

Jobs in various work fields (e.g., flying airplanes; Helmreich, 2000) require a high ability to successfully handle more than one task at a time, or to multitask. Researchers usually explain multitasking by having priorities in which individuals either attend to one task at a time, or one task receives more time processing than the other task. The current study approaches multitasking from a dynamical systems perspective. Fourteen general psychology students participated in the study by pressing a pedal attempting to maintain a steady beat and text messaging. Researchers recorded behavior over time (2 min. for each task and multitasking). The inputs to the data analysis were the X-Y coordinates of thumb movement (in pixels) over time and the recorded beat's deviation (in sec) from the metronome's beat over time. The patterns of behavior were recorded. Nonlinear analyses (Iterated Function Systems and a MANOVA on Hurst exponents for monofractality, and Wavelet Modulus Transform Maxima for multifractality) tested for fractal patterns which characterized both tasks in both conditions (single task or multitasking). Thumb movement's patterns during texting were not significantly different for single task and multitasking conditions, both displaying short–term correlations (brown noise). Patterns in tapping deviations were significantly different between the two conditions. Structure of deviations while only tapping was characterized by strong long–term correlations (pink noise); the structure while multitasking was also positively long–term correlated, but less strong. Results showed that texting and tapping behavior, as single tasks or during multitasking, are fractal.

Texting and Tapping: A Dynamical Approach to Multitasking

The ability to accomplish two or more tasks in the same general time period, or multitasking (Delbridge, 2001), seems effortless in certain situations (e.g., walking and talking) and difficult in other situations (e.g., talking and listening at the same time). Understanding and explaining performance might be straightforward when attending to a single task. Multitasking requires mental processes and skills not easily attained, which complicate the attempts to explain performance.

One proposed explanation was that when multitasking, individuals attend to only one task at a time (Broadbent, 1958). When texting while driving, for example, they either pay attention to texting or to driving. Another proposed explanation was that individuals do attend to driving and texting simultaneously. However, a decrease in both tasks' performance occurs (Kahneman, 1973). A different explanation states that driving and texting form autonomous streams of thoughts which are executed in a parallel and serial manner depending on the cognitive resources available (Salvucci & Taatgen, 2008). But what if texting and driving behavior are part of a functional system? Texting influences driving while driving influences texting. Adding more tasks or increasing the complexity of the tasks would add to the complexity of the system, thus to the difficulty to maintain quality of performance. The challenge of any viable explanation is that it needs to account not only for the humans' capacity to multitask, but also for the severe limitations in performance (Salvucci & Taatgen, 2008).

Traditional Theories

Drivers attend to other vehicles, pedestrians, and traffic signs while engaging in steering and managing the foot pedals. Nurses administer medicine to patients while following and giving medical instructions. Pilots manage a plane's panel while listening and giving instructions. The emphasis on the ability to multitask in various fields and jobs is compelling. Failure to multitask comes with great risks, however. The risk of an accident when texting and driving is four times higher than when just driving (Drews, Yazdani, Godfrey, Cooper, & Strayer, 2010). Seventy–four percent of the procedural errors made by nurses administering medicine to patients (Kalish & Aebersold, 2010) and 23% of errors in airplane piloting (Helmreich, 2000) involve failed attempts to multitask. Researchers attempted to explain successful and failed multitasking behavior (Broadbent, 1958; Kahneman, 1973). Each developed theory was built on and improved the previous theoretical and empirical frameworks.

Structural Bottleneck Models

Initial beliefs about the multitasking phenomenon stated that mental processes engaged in one task cannot engage in a second task. Processing stages (e.g., stimulus input, execution) constitute a single global channel (hence the global single–channel hypothesis) which cannot attend simultaneously to two coexisting stimuli. Individuals do not attend to both tasks, but rather switch rapidly between tasks (Craik, 1948; Telford, 1931). Adopting the global single–channel hypothesis' core idea that individuals cannot multitask, researchers intended to localize the stage where multitasking performance is constrained. Thus, a series of bottleneck models developed.

Perceptual bottleneck model (Broadbent, 1958) states that the constraints (the bottleneck) occur at the stimulus identification and meaning determination stage. The sensorial representation of the raw stimulus, its conversion to a symbolic stimulus code and meaning attribution for the converted code might impose constraints when dealing with two concurrent tasks. Therefore, individuals are forced to attend to only one task at a time (Meyer & Kieras, 1997). The most influential perceptual bottleneck models belong to Broadbent (1958), Treisman (1960), and Deutsch and Deutsch (1963). Treisman's (1960) model is an amendment to Broadbent's filter theory (1958), both recognizing the constraints occurring at stimulus identification and meaning determination stage. Treisman's (1960) model allows for all stimuli to reach conscious perception, however. Treisman's attenuation filter does allow unattended messages through the channel in an attenuated form, as opposed to Broadbent's (1958) selective (all or nothing) filter, which does not allow unattended messages through the channel. Unattended messages will be semantically processed if they meet specific characteristics. Deutsch and Deutsch (1963) extend Broadbent (1958) and Treisman's (1960) models even further by stating that there is no separate low–level filter. All stimuli will reach the same perceptual and discriminatory mechanisms and physical and contextual characteristics of the stimuli will determine their selection. Stimuli will be attended or not depending on the importance of the discrimination mechanisms. Nevertheless, semantic information passed the stimulus identification and meaning determination stage in presumed unattended auditory messages (Treisman, 1964). Thus, the option of the bottleneck residing in a different stage within the information processing arose.

Response–selection bottleneck model (Welford, 1967) starts with several basic assumptions: (a) the possibility of concurrent identification of multiple stimuli, (b) the possibility of concurrent storage of multiple stimuli in working memory (a neural system that allows the storage and processing of information required in performing a task; Baddeley & Hitch, 1974), and (c) in relation to response selection, an individual can attend to only one task at a time. When faced with concurrent tasks, the corresponding response–selection stages cannot overlap, not even temporarily. The mechanism still implies a single–channel mechanism. However, individuals can select a response for the secondary task only after selecting a response for and accomplishing the primary task (Hyman, 1953; Sternberg, 1969; Welford, 1967). Participants' response times (RTs) slowed down as the initial task's stimulus–response (S−R) compatibility (Smith, 1969) and numerosity (Broadbent & Gregory, 1967) increased, supporting the model's predictions. When varying both task's S−R numerosity and the stimulus onset asynchrony (SOA) or the distance between two stimuli presentation, however, the obtained interactions did not support the theory. Specifically, at short SOAs, RTs were not influenced by numerosity; at longer SOAs, RTs were shorter for lower S−R numerosity. These results suggest the possibility of a temporary overlap between the response selection processes in simultaneous tasks, which is contrary to the assumptions of the response–selection bottleneck model. Thus, researchers approached the next possible problematic stage, the task execution.

Movement–production bottleneck model (Keele, 1973) agrees with a simultaneous identification of multiple stimuli, concurrent storage of multiple stimuli in working memory, and response selection. When preparing and initiating individual movements successively, however, an organism can accommodate only one task at a time. The movement production stage represents the bottleneck; that is, a lower priority task must wait temporarily until the higher priority task is attended to and accomplished (Pashler, 1984). A major problem posed by the movement–production bottleneck model is the observed indirect effect that the second task factors on performance on the first task. Such findings cannot be accounted for by the model without affecting the main assumptions of the theory. Without a unitary framework and with no success in discovering where the bottleneck resides, the search continued. The idea of a central processor with limited capacity allocated to competing tasks arose; the result was the development of a series of resource theories (Meyer & Kieras, 1997).

The Unitary–Resource Theory

The unitary–resource theory does not hypothesize a bottleneck mechanism, but rather that a mental commodity required in task performance mediates multitasking. This commodity is quantifiable, divisible, and scarce (Wickens, 1991). Moreover, it can be allocated in a controllable and selective manner (Kahneman, 1973).

The unitary–resource theory is centered on four basic assumptions referring to the nature of processing capacity (Kahneman, 1973). First, attention has its limitations which vary from moment to moment. Indices of physiological arousal are correlated with the momentary limit. Second, the amount of attention allocated to a task is contingent on the demands of the task. Third, attention is divisible. At highly difficult tasks, attention becomes more unitary, however. Fourth, attention is selective and controllable, reflecting permanent dispositions and temporary intentions. Other peripheral and central structures, such as sensory receptors, memory stores, and motor effectors are also considered part of the multitasking process. Multitasking performance will decrease when concurrent tasks compete for access to the same structure because individuals face simultaneous demands on an overloaded resource of central processing capacity or mental effort.

Inconsistencies reached the unitary–resource theory also. Participants' performance in the second task (digit cancellation task) was not affected by difficulty manipulations of the primary task (visual–manual choice RT task; North, 1977). Issues such as performance insensitivity to the primary task's difficulty manipulations showed that structural interference rather than central capacity interference may constitute the primary source of performance decrements in multitasking (Meyer & Kieras, 1997). A relational approach to central and peripheral processing structures replaced the presumably counterproductive, limited central–processing capacity approach to multitasking.

The Multiple–Resource Theory

Multiple–resource theory involves distinct processing resources sets combined to accomplish an individual task (Navon & Gopher, 1979). Each processing resources set has its individual source capacity. When two tasks require access to the same resources, the tasks' demands determine the allocated resources' availability and flexibility. Individuals can attend to two tasks simultaneously; the performance in both tasks will be affected, however, due to the need to share resources. In contrast, if the tasks require two or more different sets of resources, they can be performed simultaneously without interference because the need to share resources is not present.

The concept of multiple resources seems to lack satisfactory principle constraints however (Neumann, 1987). It involves the risk of constantly revising the theory and constantly hypothesizing new capacity sources sets whenever problematic data is encountered. Such risk affects the characteristics essential to any valid theory, such as parsimony and predictive power (Meyer & Kieras, 1997). In addition, the need to explain in more detail the executive mechanisms involved in multitasking without relying on the homunculus of cognitive control became more stringent, leading to the development of the threaded cognition theory (Salvucci & Taatgen, 2008).

Threaded Cognition Theory

Threaded cognition theory conceptualizes single task or multitasking behavior as a set of processing streams of thought or threads, each thread corresponding to a current active task (Salvucci & Taatgen, 2008). These threads require access to specific sets of resources depending on the tasks' demands. An organism acquires necessary environmental information from the perceptual resources when facing one task. The information is processed by accessing individuals' cognitive resources, which in turn will guide further motor actions by accessing motor resources. When multitasking, the behavior will consist in a series of threads, with each series accessing its specific and necessary set of resources. There will be no interference from one task on the other task's performance whenever the threads access separate sets of resources and function in a parallel manner. Thus, individuals will multitask. The tasks will interfere with each other whenever the threads meet and access the same set of resources. In such cases, prioritization will occur. Thus, individuals do multitask but sporadically when attending simultaneously to two tasks at a time. In conclusion, when individuals multitask, information is processed in serial and parallel manner depending on the processing mechanisms' and resource availability.

Threaded cognition theory is an attempt to compromise the previous theories (bottlenecks and resource theories) by emphasizing an information processing mechanism that performs in both serial and parallel manner. It is also more integrative, taking into account not only cognitive, but also motor and perceptual behavioral aspects. Multitasking behavior is still a result of *independent* processing threads which feed into sets of *specialized available* resources *coordinated* by cognition, however. Behavior displayed patterns and interdependency between its components along a time continuum in different situations (e.g., human heart beat, Ivanov et al., 1999; human gait, Scafetta, Griffin, & West, 2008), suggesting a different way to approach behavior. Dynamical systems theory provides such an alternate approach to multitasking.

Dynamical Systems Theory

Lashley was one of the first psychologists to emphasize the presence of complex action sequences in individuals' behavior (Lashley, 1951). Ever since, the presence of behavioral patterns have been observed in a diverse areas, such as human gait (Scafetta, Griffin, & West, 2008), conversational head movement (Ashenfelter, Boker, Waddell, & Vitanov, 2009), or human heart beat (Ivanov et al., 1999). Dynamical systems theory approaches and analyzes behavior as a complex system whose state evolves with time. Such systems are highly sensitive to initial conditions, are self–similar, and nonlinear (Paulson, 2005).

Lorenz described the butterfly effect and emphasized how small changes could have significant consequences in time (Lorenz, 2000). A behavior's sensitive dependence on initial conditions translates into the idea that small variations within a system do not just pass inconsequently, but have long term effects. Variations change the course of the system. Although the term refers to initial conditions, one need not think in terms of beginnings and endings of behavior, just as one need not assume that a butterfly's wings flapping in Brazil is the beginning of a devastating tornado which ends in Texas (Paulson, 2005). Many factors influenced the outcome at each point in time between the flapping of wings and the tornado and a constant interaction between those changing factors generated the outcome later. Behavior, just like weather, is continuously changing. Each point in time is possibly considered the beginning of the following behavior or the end of the preceding behavior. Thus, the observed result is a continuous behavioral process that evolves in time under the constant influence of multiple variables (collective variable).

Given that behavior is a result of interactions between variables, it follows that the matter of interest is relations among those variables. From relations emerge more or less obvious patterns, a combination of components generating a consistent, iterative, and characteristic design (Kelso, 1995). Patterns can be determined and analyzed at different time scales. The greater the magnification, the greater the details observed. If a structure or a behavior displays patterns at all scales, it is characterized by self–similarity (i.e., *fractal* structure).

As observed, the shape of Britain's coast will show similar patterns whether one views it from space, a plane, or foot (Mandelbrot, 1967). Different measurement tools (e.g., a ruler, a yardstick) will generate different numbers but similar patterns. If at any magnification the structure displays the same pattern (scale–invariant), the structure is *monofractal* (Figure 1; Thelen & Smith, 1994). Snowflakes, trees, and broccoli are a few examples of monofractal structures. Most natural structures are not as simple, however. Whenever a structure displays different patterns at different scaling, the structure is *multifractal* (Figure 2). The wind and the earth's topography (Lovejoy & Schertzer, 2007) are examples of multifractal structures. Thus, simple structures display one scale–invariant pattern (monofractal) whereas more complex structures display an infinite hierarchy of fractal sets at different scales (multifractal).

Figure 1. Formation of von Koch snowflake (monofractal).

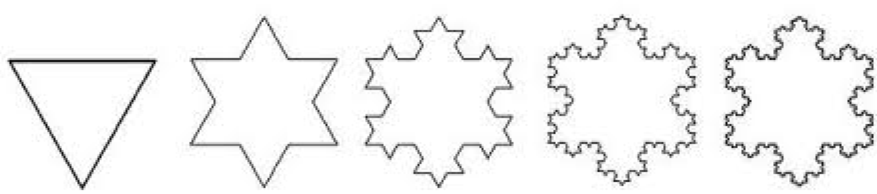
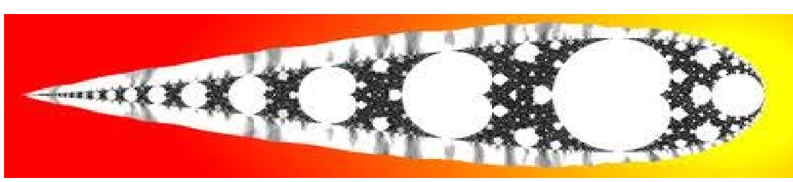


Figure 2. Mendelbrot like structure (multifractal).



Dynamical systems theory emphasizes the interactions between variables that result in a specific behavior. Feedback is an important concept whenever interactions occur, each variable being influenced by and influencing all other variables. For example, a tornado is not generated solely by wind, temperature, or humidity. It is a result of complex interactions between them. Each variable influences and is influenced by the other and assuming that either one alone caused the outcome is at least questionable. Cause–effect relations are revered in psychological research. Dynamical systems theory eschews the directionality issue by stating that the feedback loop generated by the interaction results in a circular causality, a typical characteristic of self–organizing structures (Kelso, 1995). Thus, every part of the whole is important and pinpointing only one factor as causing the outcome is erroneous and misleading.

A logical question follows. If a behavior consists of iterative, self–similar patterns, why do researchers not see the same behavior all the time? How does the change occur? The factors within the collective variable that generates the behavior are the parameters within which the system functions. Any system seeks equilibrium, a way to maintain its stability and its functionality. The system may vary within its parameters, as the factors within the collective variable change in time; it maintains its equilibrium as long as possible, however. The system is *attracted* by a specific behavior, an *attractor* being the behavior in which the system will engage given a specific set of parameters. The strength of the attractor is related to the system's stability. Enough change in any of its main interacting factors (control parameters) will lead to the system's instability or disequilibrium. The result is a change in the behavior now centered around a different attractor characterized by the new set of parameters.

A drastic change in behavior does not necessarily mean a drastic change in the control parameters (Thelen & Smith, 1994). A stable system has its critical point beyond which the system loses its stability and its attractor loses strength. When reaching the critical point, a small change in the control parameter is sufficient to destabilize the system. For example, an infant's development of walking ability does not mean, as suggested before, a sudden change in the brain's maturation (Thelen & Smith, 1994). Walking develops progressively. When walking behavior reaches its critical point (i.e., enough maturation occurred), behavior changes and infants walk. Thus, a sufficient change in one of the system's control parameters will result in a different behavior.

Linear processes are those where increasing the magnitude of one variable leads to a same amount of increase in the other variable (Lorenz, 1993). The relationship between the variables fits a straight line (hence the linearity term). Psychologists' standard statistical tools use only data that follows such a line (explained variance) and eliminates anything that falls outside the line (unexplained variance). Removed, unexplained variance can actually be characterized by a temporal and spatial structure that is overlooked by linear model analyses (Boker & Wenger, 2007). Moreover, linear analyses require random variability and independence of observations, requirements hard to meet when the data belongs to the same participant. Consequently, dynamical systems theory assumes nonlinearity of the data and provides a less restrictive statistical framework along with a more realistic conceptual one.

In conclusion, dynamical systems theory emphasizes the functional interrelation between variables by avoiding the logical fallacy of causality. Structures and behavior consist in self–similar, iterative, and dependent on initial conditions patterns. The variability within a system is just as important as its linearity. With such a matter of state, the methodological (measurements over time) and statistical tools (nonlinear analyses such as time series) also align with the theory's arguments and goals by becoming part of psychologists' tools.

Reconsidering the Study of Multitasking

The differences between traditional (e.g., bottlenecks, resource theories) and non–traditional (dynamical systems theory) explanations of multitasking seem to concern a conceptual difference that is accompanied by a methodological one. Conceptually, traditional theories consider multitasking a process initiated at cognitive level in the brain. First, bottlenecks were present at various information processing stages (e.g., stimulus identification, decision making) and did not allow individuals to multitask (Broadbent, 1958). Individuals were switching between tasks due to the serial functioning of brain processes.

Then, access to specific sets of resources and a parallel functioning of brain processes allowed individuals to multitask (Kahneman, 1973). Individuals did multitask but performance was affected whenever the concurrent tasks tap into the same resources. Threaded cognition theory (Salvucci & Taatgen, 2008) also recognizes the ability to multitask; it allows for serial and parallel processing of information depending on the processing mechanisms' availability and resources accessed.

The connecting concept of the traditional theories is the brain viewed as a collection of more or less specialized devices, each playing their part in generating behavior (Van Orden, Holden, & Turvey, 2003). Multitasking behavior starts in humans' brains and brain processes cause the observed behavior whether stages of information processing as part of a unitary processing channel or specialized sets of resources that interact or not are involved in the behavior. Any motor activity involves control and coordination ordered spatially and temporally and the brain is responsible for imposing such order (Kelso, 1995). The brain seems to rule over the other components of the system and to be the causal agent of multitasking behavior.

If the brain behaves like a keyboard for all behavior, then stimulating one point in the brain should result in the same behavior all the time. Stimulating a gorilla's cortex with the same stimulus in the same point multiple times resulted in opposite movements (i.e., flexion and extension; Leyton & Sherrington, 1917). When a drop of warm water touched a man's face he felt it as the water touched his recently amputated hand (Ramachandran, Rogers-Ramachandran, & Stewart, 1992). Such results contradict the keyboard analogy, showing an intrinsic chaotic processing of the brain. In addition, if the brain is the main controller who coordinates all behavior, the problematic issue of self–actional explanation arises: who controls and coordinates the brain?

Dynamical systems theory approaches the issue of self–actional explanation by considering systems as self–organizing (Kelso, 1995). The brain is not an entity on its own with its own intentions to generate or control behavior. The brain does not exist independently and outside context. Synergy occurs within the brain and between the brain, environment, emotions, and any other variable contributing to a behavior (Kelso, 1995). Synergies translate into patterns of behavior at various scales based on the feedback loop between variables. Such patterns imply organization. The organization is dependent on the context, thus on all variables that create the context. Sensitivity to the context and pattern formation are signs of self–organizing systems that enable flexibility and adaptability of functional behavior. Multitasking behavior is, therefore, a product of a collective variable (e.g., cognition, motor, environment, emotions), functioning as a self–organizing dynamical system.

The methodological difference between traditional and nontraditional explanations of multitasking behavior is related to the conceptual one and refers to a methodology that is appropriate to attain the conceptual goal. Linear analyses (e.g., ANOVAs, regressions) rely heavily on linearity of the data and assume that data varies along a straight line (Howell, 2007). However, if the linearity assumption is not met, data is transformed to fit the line. Measurement values larger than a specified cut–off are eliminated and the data is forced to fit the linear model by eliminating some of the variability within the data. Traditional analyses also require error terms to be independent of one another. Such a requirement is questionable when the recorded data belongs to the same participant (Gilden, 2001). In contrast, dynamical systems theory emphasizes the need to analyze variability within the data. The variability is typically nonlinear and displays fractal patterns (Boker & Wenger, 2007). Patterns develop over time. Therefore, analyzed behavior needs to be given enough time for the patterns to emerge. The need to analyze variability patterns over time led dynamical systems theory researchers to use as methodological tools recordings of behavior along a time continuum in contrast with researchers using traditional analyses that rely on recorded behavior at specific and isolated moments in time. Thus, snapshot recordings can provide limited information about the behavior at certain moments in time and no information about the process occurring between two moments, while analyzing behavior over time provide researchers with the missing between moments information.

Nonlinear behavior recorded in time can be analyzed using time series analysis as a statistical tool (Tabachnick & Fidel, 2004). Time series analysis does not rely on averages or other measures of central tendency (Carello & Moreno, 2005). It is possible, for example, to have two samples with similar means but different distributions and variability within the data. It is also possible to have two samples with significantly different means but a very similar distribution of the variability within the data. Conventional analysis would consider the first example as samples belonging to the same population and the second example as belonging to different populations. But how accurate are traditional statistics? If learning how to tie a shoe is an infants' goal, infants could indeed achieve that goal in an average amount of time. The way to reach the goal, however, will be different and unique for each infant. Conventional analyses do not use such uniqueness. Nonlinear dynamical systems analysis (e.g., Fourier, Wavelet Transform) studies the unexplained variability. It studies the dreaded noise which is eliminated from conventional analyses. It does not look for differences between means, but rather how each series' mean varies and how it relates with the time series at different scales. Thus, nonlinear analyses use more of the dependent variable measurements and offer a more realistic perspective on recorded data than linear analyses.

The Current Study

The current study approached multitasking through a dynamical systems theory perspective. The tasks involved motor activity. Participants texted, tapped in an attempt to maintain a steady beat, and simultaneously texted and tapped. Researchers recorded behavior over time (2 min. allocated for each task performed individually and for multitasking). Researchers hypothesize that multitasking behavior is a complex dynamical system with subsystems that interact in different ways at different levels. The interaction results into a self–organized pattern that reflects a nonlinear process. Nonlinear analyses (Hurst exponent and Iterated Function Systems for monofractality, as well as Wavelet Modulus Transform Maxima for multifractality) tested for fractal patterns which will characterize both tasks in both conditions (single task or multitasking).

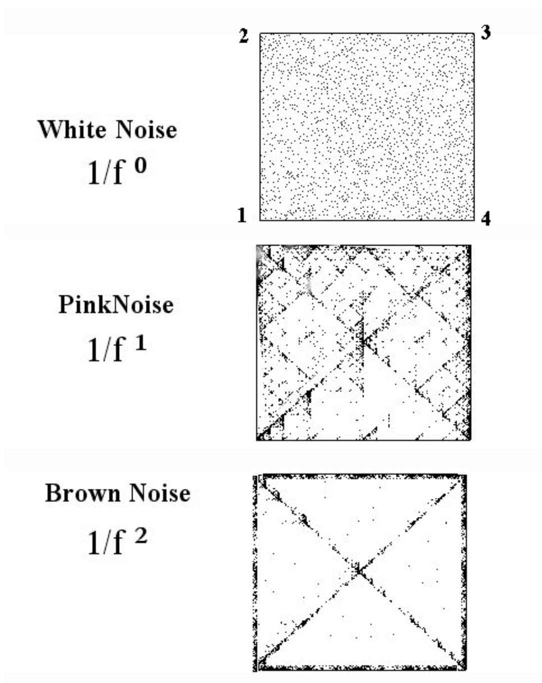
The Hurst Exponent

The global Hurst exponent (*H*) is a symbol of monofractality that measures the strength of the long range correlations within the time series. That is, *H* shows the dependence between sequential data points in time. *H* describes also a system's complexity, different *H* values being associated with more or less complex systems (Munoz-Diosdado, 2005). *H* is obtained by estimating the dependence of the rescaled range (a measure of the time series' variability and its fluctuations with the time scale) on the time span of the series being considered. A time series is divided into shorter time series, the average rescaled range being calculated for each resulting short time series (Jens, 1988). An *H* of or close to 0.5 would be interpreted as no relationship between data and an *H* of or close to 1 would be interpreted as a highly complex relationship between data (Scafetta et al., 2008).

Iterated Functions System (IFS) Clumpiness Test

The IFS clumpiness test is an alternate way to determine the presence of temporal correlations within the time series (Aks, 2005). IFS provides a visual representation of present or absent fractals by generating clumped patterns of colored noise and filled spaces based on correlations within the data. Different degrees of correlation generate different noise colors (*1/f* noise; Figure 3). Noise follows a *1/f* scaling relation (Gilden, 1997) and implies an inverse relationship between temporal scales and frequency. The higher the scale, the lower the frequency of a signal and vice versa. White noise ($1/f^0$) is represented by a pattern characterized by homogenously filled in spaces and it describes the absence of a correlation within the time series (also known as random walk). Brown noise ($1/f^2$) is represented by a pattern characterized by dot concentrations along the diagonals and some of the sides of the representational space (squares); the rest of the space is left empty. Brown noise suggests a short term history within the time series; that is, the influence of one data point on the following data points dissipates after a short amount of time. Pink noise ($1/f^1$) is represented by a pattern characterized by different size, repeating self–similar triangles dispersed along the diagonals of the squares (Aks, 2005). Pink noise involves a long–term correlation within the time series; that is, the influence of one data point persists across the time series.

Figure 3. Example of IFS output for white, pink, and brown noise data (Aks, 2005).



Wavelet Transform Modulus Maxima (WTMM)

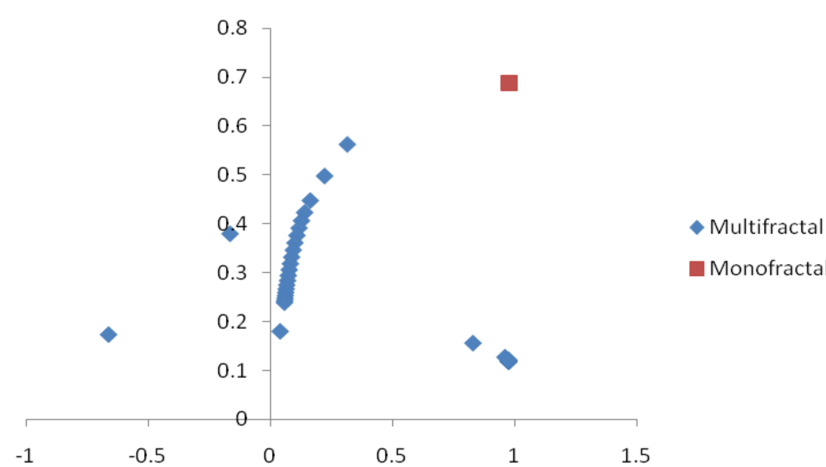
Complex patterns and signals can be successfully analyzed by decomposing them in different frequencies. The most popular frequency domain analysis is the Fourier transform that analyzes signals whose frequency content do not change in time (stationary) or at different scales (monofractal) and provides a time–frequency representation of a pattern or signal. If the signal's frequency varies in time (non–stationary) or at different scales (multifractal), a WTMM is the appropriate analytical tool, providing a time–frequency representation of the signal (Jouck, 2004).

WTMM tests the time series on multiple scales by parsing it into segments (wavelets) and compare them to a one–dimensional mother wavelet, a prototype function of the entire series. All segments are then compared with the mother wavelet at all scales. Then the wavelet is stretched (dilated), and the same procedure repeats at all scales. The higher the dilation, the longer the segment of time series to which the wavelet is compared. Dilation allows detection of persistent singularities or irregular structures, which often carry the most important information in a signal (Mallat & Hwang, 1992). Dilation generates similarity coefficients that reveal the degree of similarity between the mother wavelet and the time series wavelets. The thermodynamic partitioning function determines the number and the strength of the local maxima (the segment with the highest similarity) at each scale, based on the similarity coefficient series.

Next, WTMM generates a function based on the partitioning results. The newly generated function estimates the multifractal dimension, focusing on scaled wavelets' local maxima. The Hölder exponent (*h*) is calculated based on the scaling of wavelet transform coefficient across all scales. The absolute values of the similarity coefficients are arranged in a two–dimensional time–scale matrix, with time point in the signal and frequency scale as the two dimensions (Robertson, Farrar, & Sohn, 2002). The log of the frequency spectrum of the signal at the first time point (the first column of the matrix) is then plotted against the time scale at which the wavelet is calculated. The resulting slope is the signal's *h* for the first time point. The same process is repeated for each time point of the wavelet modulus (Robertson et al., 2002).

The Hölder exponent measures rapid changes of the time series singularities and their strength (Scafetta et al., 2008). When the time series is monofractal, *h* will be the same as *H* because the series has one attractor. When the time series is multifractal, different time scales have different attractors, thus *h* will be different than *H* and will become the local version of *H* (Enescu, Ito, & Struzik, 2006). The statistical distribution of *h* is plotted with *h* on the X axis and the *D(h)* (fractal dimension of the attractor) on the Y axis (Van den Berg, 2004). Monofractal data will be represented by one fractal exponent; therefore, the *D(h)* plot will show one point. Multifractal data will be represented by an arc across *h*, showing that *the* attractor's strength varies in time (Figure 4). The maximum possible value of *D(h)* is one, which would indicate that *h*'s strength is present throughout the entire signal.

Figure 4. Hypothisized monofractal Cantor set and multifractal WTMM distribution.



Researchers in the current study approached multitasking from a dynamical systems perspective and used nonlinear statistical analyses to analyze the data. Hurst exponent and IFS tested for monofractality and WTMM for multifractality. Thus, researchers applied a new methodology to show an alternative theoretical explanation to multitasking behavior and performance.

Method

Participants

Participants were 14 undergraduates (mean age = 21, *SD* = 3.37) who participated in exchange for course credit. All were at least 18 years old, had normal or corrected vision, and were right–handed. Twelve reported English as their first language. Data from 6 participants were excluded because of technical difficulties. Only one participant reported experience with drums.

Materials

The task involved attempting to maintain a steady beat with a mechanical drum pedal while text messaging. The drum pedal was a PDP Single Pedal model SP400 chosen for its ease of use, versatility, and lateral stability. The impact of the pedal on 61x14x14 cm wooden block generated the sound. The block was 5 cm from the pedal, parallel with the front side of the pedal support. The sound of the pedal striking the block was recorded with a Dynex microphone model DX–54. The LG cell phone model CF360 used for texting had the following features: 262K Color TFT, 320 x 240 Pixels, display dimensions of 3.97” (H) x 1.89” (W) x 0.665” (D); and a weight of 3.51 oz. Video of the session was recorded with a 15 megapixels Sony camera on a tripod. Appendix A shows these materials.

Free, open source software from Audacity (Audacity, n.d.) sampled the drumming sound at a rate of 60 kHz with 32 bits per sample. MaxTRAQ motion analysis software (MaxTRAQ, n.d.) can track a designated object in a video recording. In the current study MaxTRAQ tracked the participants’ thumb movements along the X and Y coordinates at a sampling rate of 30 frames per second. The Automatic Tracking feature allows frame–by–frame analysis of movement measurements (e.g., distance between points, angles).

Procedure

Each participant listened to a short description of the tasks then practiced using the mechanical drum pedal and the text feature of the cell phone separately until he or she reported feeling confident enough to use both instruments. Necessary adjustments to the position of the video camera, the drum pedal, and the chair were made during the two–minute practice session.

Participants spent two minutes on each of three tasks: texting only, tapping a beat only, and simultaneously texting and tapping. The order of the initial task (tapping or texting) was counterbalanced between participants; multitasking was always the final task. The texting task involved producing the same message, “I am a general psychology student at the university of central oklahoma,” as many times as possible in 2 minutes. Before texting, participants repeated the message aloud until they could say it three times without error. They were to ignore errors of spelling, punctuation, capitalization and to use only their preferred hand, and not to rest their hands on their legs while texting (to eliminate the interference of leg movements). MaxTRAQ tracks objects according to contrast, so a black Velcro strap (4cm long x 1cm wide) with white Velcro squares (with a side of 80mm) was wrapped around the texting thumb. One white square was designated as the tracking target. The tapping task involved maintaining a steady beat by pressing the drum pedal with the preferred foot. Participants listened (via headphones) to a metronome set at 60 beats per minute, a beat they were to match by tapping the pedal on the wooden block. The multitasking condition involved attempting to simultaneously perform the texting and tapping tasks following the same instructions–texting the same sentence and keeping the metronome’s steady beat.

Data analysis

The inputs to the data analysis were the X-Y coordinates of thumb movement (in pixels) over time (3600 data points per participant; Figure 5) and the recorded beat's deviation (in seconds) from the metronome's beat over time (120 data points per participant; Figure 6). A positive deviation indicated a late beat and a negative deviation indicated an early beat. Thumb movement data had to be transformed into integers, and a constant five (higher than the range) was added to each deviation score to eliminate negative numbers for analysis purposes. All final deviation scores were positive numbers.

Figure 5. MaxTRAQ output for thumb movement.

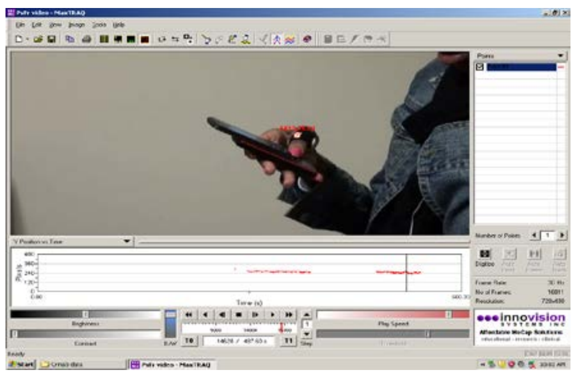
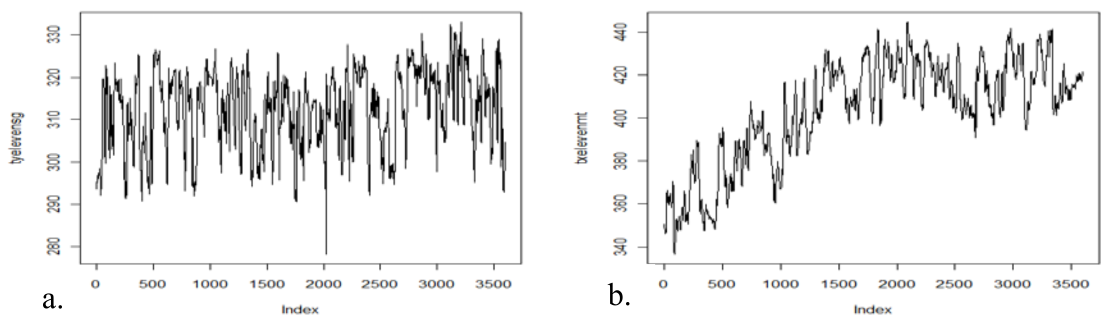


Figure 6. Audacity output for the foot beat recordings.

Researchers examined the time series data for signs of fractal structures. Figure 7 displays an example of time series for one participant's horizontal thumb movement in single task and multitasking condition. Behavior over time (2 minutes) is plotted with time (in milliseconds) on X axis and distance in pixels on Y axis. R statistical language aided in the examination. The *H* value for each participant's horizontal, vertical thumb movement time series and beat deviations time series was computed. Next, a multiple analysis of variance (MANOVA) tested the statistical significance of the difference between the average *H* of single task and multitasking data. An IFS test also helped in our search for fractals in the time series, providing a visual representation of the complexity of the underlying structures.

Figure 7. Time series example for horizontal thumb movement: (a) single task condition and (b) multitasking condition.



In addition, a WTMM analysis determined the presence of multifractal structures for the horizontal and vertical thumb movement time series and the *D(h)* plot was obtained. Beat deviation scores did not enter the WTMM analysis due to insufficient amount of data points. The inherently discrete empirical data (Audacity software samples at a 60KH rate, MaxTRAQ software at 60 frames/sec.) entering the WTMM analysis was converted to a continuous form by a continuous one–dimensional wavelet transform that was applied to the variation of the time series. The transformation also ensured consistency with the underlying mathematical structure of the analysis (Ashenfelter, Boker, Waddell, & Vitanov, 2009).

Results

Hurst exponent and MANOVA

H was computed for each participant's dependent variables (DVs), for each level of the independent variable (IV) to search for monofractal structures. The time series was whitened before entering the analysis in order to reduce measurement errors usually occurring due to human and equipment error and imprecision. The means and *SD*s of *H* calculated for all DVs are presented in Table 1.

Table 1: Means and *SD*s (in parentheses) for thumb movement data (on X and Y axes, in pixels) and foot beat deviations (in seconds).

	X axis	Y axis	Deviations
Single Task	1.36 (0.04)	1.35 (0.03)	1.01 (0.30)
Multitask	1.34 (0.04)	1.40 (0.20)	0.8 (0.12)

A one–way within subjects MANOVA was performed on the *H* for the three DVs: horizontal thumb movement, vertical thumb movement, and beat deviations. The Task condition was the within participants independent variable with two levels: single task and multitasking. DVs entered the analysis simultaneously to protect for Type I error rate. Mauchly's test checked the sphericity assumption, which was not violated, showing that the matrix had approximately equal variance and covariance. There was no significant multivariate effect.

The univariate Analysis of Variance (ANOVA) revealed a significant main effect for beat deviations *H*, $F(1, 13) = 5.82$, $p = .03$, $\eta_p^2 = .31$, observed power of .61. Multiple comparisons analysis showed that H values for the single task condition ($M = 1.01$, $SD = 0.30$) was higher than *H* for multitasking condition ($M = .80$, $SD = 0.12$). In multitasking condition, patterns of deviations from the beat were complex, but less cohesive than the patterns in the single task condition. There were no other significant findings.

IFS Clumpiness Test

For a visual representation of *H*, an IFS clumpiness test was also performed on participants' time series. IFS showed brown noise for horizontal (Figure 8) and vertical movement in single task and multitasking conditions. A difference emerged within the beat deviations DV. IFS showed results resembling pink noise for both conditions (Figure 9); the single task condition was closer to pink noise than the multitasking condition however, involving a lower strength of the attractor.

WTMM

The WTMM provided evidence that when texting and tapping, thumb movement (horizontal and vertical) displays scaling regions of self–similarity over time, and that different fractal structures characterize different scales of the behavior. If the behavior would be monofractal, results would show only one singularity exponent for the whole time series and one point on the *D(h)* plot. The current study's time series showed many subsets characterized by different local exponents, the *D(h)* plots illustrating the specific arc shaped trajectory for each participant's horizontal and vertical thumb movement series. Figure 10 contains *D(h)* plots for two of the participants' thumb movement. First, fractal dimension (which is related to degrees of freedom of a system) decreased with an increase in attractor strength. Second, the highest levels of fractal dimension were related with the moderate strength attractors. Third, dimensionality also decreased when the strength passed a minimum level of attractor strength. Thus, texting and tapping behavior are intrinsically complex and nonlinear.

Figure 8. IFS clumpiness test results for one participant's horizontal thumb movement in single task condition. The clumping pattern indicates brown noise.

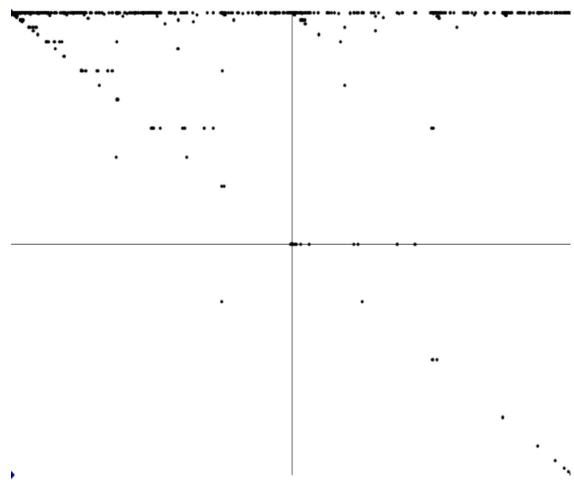


Figure 9. IFS clumpiness test results for one participant's foot beat deviations in single task condition. The clumping pattern indicates pink noise.

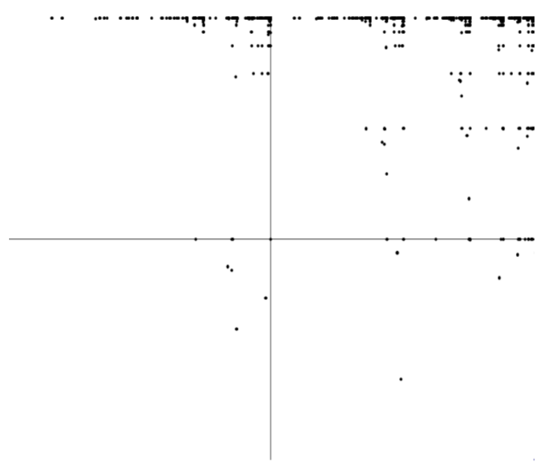
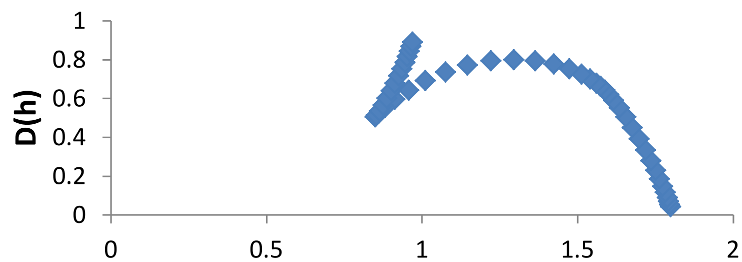
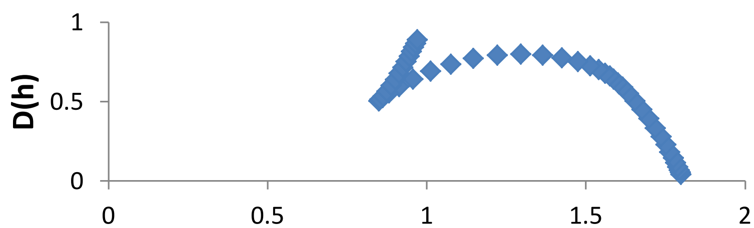


Figure 10. D(h) plots for a participants’ (a) thumb movement on X axis for single task condition and (b) multitasking condition.



a. **Attractor strength (h)**



b. **Attractor strength (h)**

Discussion

Multitasking behavior does show fractal characteristics. That is, depending on the scale at which behavior is analyzed, patterns in behavior occur. When performed individually or simultaneously texting and tapping revealed fractal patterns with texting behavior revealing different patterns at different scales (multifractality). The MANOVA results showed a significant difference only for the beat deviations time series and not for the horizontal and vertical thumb movement. Horizontal and vertical thumb movement display fractal patterns, however. *H* mean values (approximately 1.35) for both conditions on both DVs are close to 1.5 which is a sign of brown noise ($1/f^2$). Thus, horizontal and vertical thumb movement show short–term history within the time series meaning that each data point has an effect on the following data points and is influenced by the previous ones. The short–term characteristic implies a high complexity level of the behavior given that the strength of the positive correlations or attractors dissipates rather quickly in time. Beat deviations also show fractal characteristics with *H* values for single task condition distributed around the mean of 1.01 and H values for multitasking condition distributed around the mean of .80. The two *H* values are significantly different. Both behaviors have *H* values close to 1 which indicates pink noise ($1/f^1$). The multitasking condition is closer to a white noise, however. Beat deviations during single task condition seem to be highly structured and complex, clustering around a highly strong attractor. Each data point displays a long–term history by having a long–term effect on the following time series.

IFS clumpiness test figures aid in better observing the fine structure of the time series by distinguishing between different noise colors and associating it with specific noise and correlations. The IFS test supports the observed *H* values; the points cluster along the diagonals and some on the sides of the square for horizontal and vertical thumb movement. IFS test shows pink noise for beat deviations in single task condition; the dots cluster in repetitive triangles along the diagonals. IFS test also shows pink noise for the multitasking beat deviations. Even if the dots are still clustering in repetitive triangles along the diagonals, they are less structured. That is, the attractor strength weakened. There is a complex, structured long–term fractal pattern; its strength and cohesiveness, however, decreases during multitasking.

WTMM provided evidence for that texting behavior is multifractal. Horizontal and vertical thumb movement behavior is characterized by different patterns and different attractors at different scales. Attractors' strengths are related to the system's fractal dimensionality and degrees of freedom. Fractal dimension level decreased with strength. That is, an attractor's strength along with its influence on behavior increased with a decrease of degrees of freedom. The highest levels of fractal dimension related to moderate levels of attractors' strengths. Thus, increased degrees of freedom result in high adaptability needed when the system functions at its criticality points. Fractal dimension along with degrees of freedom decrease when an attractor's strength passes a minimal threshold. The decrease implies that behavior is highly dependent on task's demands. Thus, texting behavior is a complex behavior with nonlinear, multifractal characteristics.

Results showed besides fractality in all tasks in all conditions that when attempting to text while maintaining a steady beat participants are not as affected in their texting behavior as they seem to be affected in their tapping behavior. Adding an extra motor task (which increases cognitive load) does not seem to affect texting behavior. Participants show similar patterns in texting in horizontal and vertical thumb movement. Tapping seems to be more affected by adding an extra task however; the behavior is highly structured when solely tapping and with a weaker structure while multitasking. Participants' deviations patterns were significantly different in multitasking and single task condition.

A reasonable explanation for the current study's results would be that texting behavior is a commonly encountered behavior. Participants might have much more experience with the task. Consequently, having more experience with texting (which is a behavior commonly performed along with other tasks such as driving) might lead to an increased similarity in thumb movement patterns in both conditions. Tapping is not such a commonly encountered behavior; for example, only one participant in the current study mentioned having any experience in drumming. Thus, participants' lack of experience with the task might have made a difference in the pattern's strength in tapping; the pattern's structure loses strength and becomes easier to break while multitasking. Drummers might display a more similar pattern in both tasks. Future studies should take experience with the task into account.

Another possible explanation relates to the materials used to generate and record the behaviors. Participants might have found the mechanical pedal hard to press, especially during multitasking, which occurred between three and five minutes after performing at the single task. Fatigue due to participants not being accustomed with the task's physical demands might have played a role in the multitasking performance. Also, MaxTRAQ's ability to track the thumb movement was not always present; the program did not constantly track the specified point. In a few situations, the program lost the tracked point and researchers had to manually track it, frame by frame, for a certain amount of recording time. Researchers' intervention can add noise in the time series, noise that will be integrated in the performed analysis.

Using time series analyses gives the current study a great advantage. Recording behavior on a time continuum provides more detailed information about the studied behavior. In contrast, other methodologies provide just a few frames of a continuous behavior. Time series not only provides the information that traditional methodologies do but it also fills the missing behavior. Such behavior is usually disregarded and forgotten. Traditional methodology assumes that behavior recorded at specific points in time reflects the behavior occurring between those points. The current study's methodology eschews such an assumption by taking into account the dynamical characteristics of behavior.

On a conceptual level, dynamical systems theory states that multitasking is a system characterized by sensitivity to initial conditions, fractality, and nonlinearity. Results showed the presence of short–term history for the texting behavior, and long–term history for tapping. Any type of history involves correlations between the data points and a change at any point in the time series might result in a more or less observable change in the following behavior. If everything affects everything else and everything is related within a system, then any change in a variable will result in a change in the outcome. This is the main idea of sensitivity to initial conditions which seems to hold true in this case.

A dynamical system is also fractal. It consists in self–similar structures, which might be the same or might vary at different scaling. Results showed fractality within all DVs. The behaviors showed an intrinsic correlation. Each thumb movement influenced its own following behavior while each foot beat in tapping influenced the following beat. The relationship persisted in time. Thus, the second characteristic of a dynamical system is met.

Pink and brown noise imply that local means and *SD*s of the time series depend on the sample of the time series that is analyzed. White noise implies that local means and *SD*s are representative of the population (Holden, 2005). While linear statistical analyses' assumptions require the presence of white noise in the sampled data, therefore a random variability independent of the other observations, pink and brown noise wear the signs of nonlinearity. That is, correlations within the one participant's data violate the independence of observation assumption. The current study's results showed presence of pink and brown noise in the DVs. Therefore, another characteristic of dynamical systems is displayed.

The studied behaviors displayed sensitivity to initial conditions, fractal patterns, and nonlinearity. These are all characteristics of a dynamical system. Fractals are related to self–organization. Dynamical systems theory assumes that any behavior, including multitasking, is a more or less stable and complex self–organized system. No causal agent is present, yet organization occurs. If traditional theories have a self–actional, directional approach and consider that all coordination and control reside within one's brain, dynamical systems theory does not adhere to such a view and leaves the system's organization to its components. The current study showed that both behaviors organized themselves in correlated structures. Each frame within each behavior influenced the following behavior and at a larger scale, one task interacted with the other. Thus, considering the brain as a single coordinator of the behaviors would be questionable. The brain is one component of the system and its role in the system's functioning exceeds the purpose of this study. If motor behavior can generate its own patterns at a milliseconds level of vertical and horizontal thumb movement, it seems reasonable to assume that the brain is not the only coordinator of the system. Interaction and self–organization are the key with the behavior being a result of all the system's variables.

Searching for fractal characteristics in the two behaviors is a first step in a dynamical approach to multitasking and literature in the field lacks such a perspective on the phenomenon. More details about both behaviors and their interactions can be obtained given the expanding list of available data analysis. Patterns for both behaviors could be superimposed (e.g., by using crossed windowed correlations) with the goal to observe how one behavior's patterns change as a function of the other behavior's pattern. Researchers could observe the changes in variability within the different tasks' time series and the interrelationship between them. For example, just as healthy heart's beat has been shown to be irregular and to reduce its variability and become more regular before a heart failure (Ivanov et al., 1999), the same trend could be observed within multitasking. It is highly possible that the amount of variability within the data increases when individuals are multitasking, whereas variability decreases before the system crashes. Discovering the intricacies of behavioral systems involved in multitasking can provide valuable knowledge within the human factors field. Observing how individuals multitask and what parameters delimitate one's ability to multitask increase the possibility of creating technology that would accentuate our strengths and compensate for our weaknesses in multitasking performance.

Bottleneck models suggest that individuals switch between texting and tapping. Resources theories suggest that resources are being allocated to one task (texting for example) resulting in a depletion of resources allocated for the other task (tapping). Threaded cognition theory suggests that texting and tapping sometimes are performed simultaneously and sometimes individually. Dynamical systems theory suggests that texting and tapping are part of a system and they interact with each other and with other variables. How does this system function, however?

The system is guided by a collective variable which sets the control parameters within which the system functions. They form a coalition of constraints which dictated the multitasking behavior. The motor system allows individuals to perform the tasks by providing the mechanical mechanism involved in the multitasking behavior. The motor system regulates individuals' capacity to coordinate motor behavior (Carson, 2004). The brain provides the neural structures that aid in the motor activity. Muscle synergies directly influenced neural activity in the context of limb coordination (Carson & Riek, 2000). Thus, neural structures are sensitive to the muscle synergies that are involved in the observed motor behavior. Attention also influences motor coordination (Scholz & Kelso, 1990) and neural activity in its attempt to maintain stability in coordinated motor behavior (Temprado, 2004). The result is a circular causality between attention and coordinated motor behavior such that they constrain reciprocally. Tasks demands dictate which muscles are required to perform the tasks, requirements which will reflect at neural level. Intrinsic and extrinsic variables are interrelated and each depends on the others. The system is context dependent and functions based on the feedback loops generated by the variables. A sufficient change in any variable leads to a change in behavior. A change in behavior translates into a change in performance. The observed result is multitasking behavior with varying performance across the task.

In conclusion, multitasking behavior showed the main traits of a dynamical system. Studied behaviors showed sensitivity to initial conditions, fractality, and nonlinearity. Thumb movement's patterns during texting were not significantly different for single task and multitasking conditions. Both displayed short–term correlations. Patterns in deviations in tapping were significantly different for the two conditions. Structure of deviations while only tapping was characterized by strong long–term correlations. The structure while multitasking was also positively long–term correlated but less strong. These results, while being interesting, leave room for more questions. The emphasis falls on how the structures look like, what are their controlling parameters, etcetera. However, researchers should distance themselves from the mathematical intricacies and attractive, eye–catching visual effects of fractals, and ask themselves: what do they mean? The meaning might be more profound and complex than all the mathematical underlying structures. Until the question is answered, dynamical systems theory will keep researchers' interest alive, the search for fractals continuing.

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Appendix A

Materials

PDP SP400 Single Pedal

Dynex DX-54 microphone

LG CF360 model cell phone

Sony recording camera