Modelling Mind Wandering in the Metronome Response Task

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Abstract

Mind Wandering (MW) is a phenomenon that has drastic implications for performance on tasks requiring sustained attention. Despite this importance, the mechanisms of MW are loosely examined. In a prior paper, a MW model was created which could model the empirical data obtained in the SART. To test the robustness of the MW theory in this model, we investigate whether the theory can be used to model human performance in the MRT. To test our hypothesis, we created two models in ACT-R to simulate perfect human attention and MW accordingly. The analysis revealed that there was no significant difference between the performance of our models and human data. Thus, we can conclude that the MW theory in the previously created model is sufficient for modelling empirical data in the MRT. Despite this result, it is unclear whether our model utilizes the exact mechanisms as human subjects.

Keywords: Mind Wandering; MRT; Timing; Temporal; Cognitive Model; ACT-R

Introduction

Mind Wandering (MW), the act of ”zoning out” when performing a task, is a ubiquitous phenomenon since it occupies over 50% of our thoughts during waking hours (Killingsworth & Gilbert, 2010). In addition to its near omnipresence in life, research suggests that MW can severely harm performance on tasks which require sustained attention (Mooneyham & Schooler, 2013).

To our knowledge, most research on MW revolves around the Sustained Attention to Response Task (SART) in which participants must withhold response to an infrequent target while pressing a button in response to a frequent stimulus (Bastian & Sackur, 2013; McVay & Kane, 2009; Mrazek et al., 2012; Seli et al., 2018). As highlighted by Seli et al. (2013), there are criticisms associated with the SART as the test primarily serves as a measure of one's ability to inhibit responses, rather than to provide an estimate of one's likelihood to mind wander due to the nature of the infrequent stimuli. Participants must also respond to a stimulus as quickly as possible which could lead to different responses depending on how the subject trades speed with accuracy.

In order to remedy these limitations, Seli et al. (2013) introduced the Metronome Response Task (MRT) in which subjects had to press a button in rhythm with a steady beat. The instructions were relatively simple: the button had to be pressed synchronously with the beat. A measure known as the Rhythmic Response Time variance (RRTv) was created to analyse the differences in response times. This measure calculated the natural-log transformed response variance to a beat in the five trials before a randomly placed thought probe. The log transformation was necessary since the raw response variance was non-normally distributed which hampered the power of statistical tests. With this metric, the authors demonstrated that subjects who were mind-wandering tended to display higher levels of RRTv compared to others. Thus, RRTv could be claimed as a predictor of mind wandering in the MRT.

Several other studies have reached the same conclusions as the original paper (T. Anderson et al., 2020; Meier, 2018; Seli, Cheyne, et al., 2015; Seli, Jonker, et al., 2015). However, we are unaware of any model created to simulate mind wandering on the MRT task. Nonetheless, van Vugt et al. (2015) has implemented the creation of a MW model in the cognitive architecture ACT-R (J. R. Anderson et al., 1997) for the SART. This model simulates mind wandering as the competition between an attend goal and a wander goal. During the attend state, the model pays close attention to the task while simultaneously checking its current goal. In this state, it is possible that the wander goal would eventually have a higher priority than the attend goal which compels the model to mind wander. The model still performs the task during the MW state, albeit less effectively since attention is directed towards retrieving random memories. One of these retrieved memories reminds the model to return to the attending state. Using this model of MW, van Vugt et al. (2015) have had considerable success in modelling empirical data in the SART. Thus, it would be interesting to see if this implementation of MW could explain the RRTv of empirical data in the MRT.

Therefore, for the purpose of filling in the void in the current literature, we seek to answer the following research question: Can the mind wandering implementation proposed by van Vugt et al. (2015) model the Rhythmic Response Time variance of subjects in the Metronome Response task? To answer this question, we will create two separate models to simulate human RRTv in the MRT when paying attention and mind wandering. We expect the RRTv of the mind-wandering model to be higher than the attentive one. In addition, we expect both models to possess a similar RRTv compared to the empirical human data. The remainder of this paper will detail the structure of our model along with our methods of obtaining performance data. Finally, we will assess our hypothesis using the obtained data and discuss our findings.

Model

We will use the cognitive architecture Adaptive Control of Thought - Rational (ACT-R) to simulate mind wandering in the MRT. This architecture uses several components which perform high-level cognitive functions. In addition, ACT-R contains an interface to create experiments which can then be administered to the models to collect performance data. Another important aspect that motivated our decision to use ACT-R is the existence of its temporal module which will aid the model in keeping track of time during the MRT.

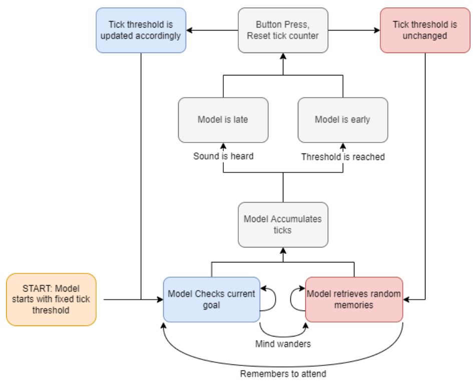

Figure 1: Flowchart of the model. The states in blue and red are unique to attending and MW respectively which determines whether the model is able to learn the metronome's rhythm after a button press. All other states are common to both conditions.

Time keeping in ACT-R

The temporal module in ACT-R makes use of a noisy estimate of time known as a tick. More precisely, the length of a tick is defined as $t_n = a * t_{n-1} + noise(mean = 0, sd = b * a * t_{n-1})$ where t_n represents the time period of the current tick, a is a multiplier and b represents a noise factor (Taatgen et al., 2007). A feature of this system is that once enough time has passed with the current tick value, the tick counter is incremented and the newer tick lasts for a longer period of time. For example, suppose the tick counter possesses the value of 1. After 11 ms, this value becomes 2. Once another 12 ms pass, it further gets incremented to 3.

In order for the model to respond rhythmically, we need some way to match the number of ticks to the corresponding interval between metronome beats. To solve this issue, we set a threshold in the goal buffer of the model. Once the tick counter is greater than this threshold, the model can give a response and reset the counter. At the start of the experiment, we will set this value to 27 since it represents the theoretical estimate for the interval between beats in the MRT. We obtain this value by using a geometric progression using the above formula. Since subjects in the MRT gain experience with a trial run beforehand, we expect them to gain an understanding of the rhythm of the task. Thus, it seems logical to also start the model with a suitable threshold. Since the tick system is noisy, we expect this threshold to change drastically as time progresses in the experiment.

Model Description

We will create two models to model empirical data in the MRT. One model will solely stay focused on the task and will be compared to the on-task performance of humans. The other model will utilize the same mechanisms as the standard model, however, it will also possess the ability to mind wander which will be built on van Vugt et al. (2015). The RRTv of this model will be compared to the RRTv of humans who were mind wandering during the task. Creating the models in this manner gives us a straightforward way to obtain data which can be compared to human performance.

Both models will make use of ACT-R's temporal module for pressing a button in rhythm and will also utilize the aural buffer to correct itself and react to the beats of the metronome. When the experiment starts, the models start to accumulate ticks and give a response either when the tick counter exceeds the threshold or when a beat is heard. The tick threshold for pressing the button is then immediately updated based on whether the model was early or late compared to the beat. This allows the model to learn the beats of the metronome. For instance, if the tick threshold was 27 and the model was late because it had to react to the beat, then the threshold is decreased to 26. Conversely, if the model was early because it used its internal rhythm, then the tick threshold was increased to compensate. It must be noted that this learning of ticks only occurs when the model pays attention to the task. We expect the learning of ticks to be an intensive process which would not be executed during mind wandering.

Transition between Cognitive States

Depending on the state of the model, different actions occur which enable the mind-wandering model to transition from one state to the other. This does not apply to the attending model since it only possesses a single state. When the mind-wandering model is paying complete attention to the task and learning the rhythm, it is in the attend state and continuously check its current goal. If the goal retrieved from the declarative memory is to mind wander, then it enters the wandering state. Here, the model does not perform the intensive process of learning the rhythm. Nonetheless, it is still able to hear and respond to the beats of the metronome. In the MW state, the model performs the task while simultaneously retrieving random memories from the declarative memory. One of the memories compels the model to return to the attend state. This implementation follows the same process as van Vugt et al. (2015).

Methods

In order to evaluate our model, we needed to create a version of the MRT task in ACT-R. We attempted to mimic the MRT by Seli et al. (2013) since we would compare our model with the empirical data generated by the study. Thus, the beats were spaced apart with a 1300 ms gap with each beat persisting for 75 ms. It must also be noted that 18 probes were randomly placed inside blocks of 50 beats each. The five beats before a probe were used to compute the RRTv of the model as this was the same process used in the original MRT. We needed to calculate the RRTv since it is the metric that we will use to quantitatively compare our model with empirical data. To this end, we recorded the onset time of each beat along with the corresponding time at which the model gave a response. We also recorded the tick threshold of the model when it gave a response along with the activation values of the attend and wander state to qualitatively assess the model.

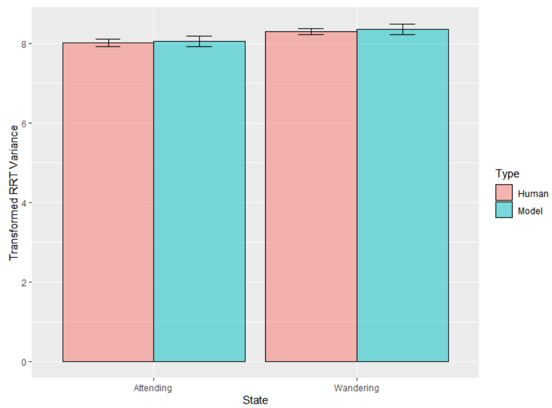

Figure 2: Average RRTv of our models when compared to empirical data from Seli et al. (2014).

We repeated the experiment 74 times each with the attending model, which always learnt the rhythm, and the MW model, which did not learn the rhythm during MW. This sample size is equivalent to the number of participants in Seli et al. (2014). This paper is an extension of the original MRT paper which we will use for comparison since it directly reports the mean RRTv. We believe that both of our models are biologically plausible since they are built using established ACT-R models and only possess knowledge that a human would have.

It was necessary to reduce the noisiness of ticks in both models to match human RRTv. This has the effect of letting the model keep track of time more precisely which seems justified if human subjects in the MRT were more skilled at timekeeping than the average person. We performed this fine-tuning by first determining the required value for the attending model. It seemed logical to give the same noise value to the MW model since the mechanisms for performing the task were identical. In addition to the change in temporal noise, we also needed to reduce the rate of MW in the MW model to match human performance. This was done by reducing the base-level activation of the wander chunk. We made this change in accordance with Forster and Lavie (2009)'s observation that MW occurred less during intensive tasks.

Results

Our research question seeks to determine whether van Vugt et al. (2015)'s theory of MW can model human RRTv in the MRT. Thus, in order for our models to be comparable to the empirical data of Seli et al. (2014), we need to satisfy two constraints. First, the RRTv of our MW model must be higher than the attending model since human RRTv was higher during MW. In addition, there should be no significant difference between the performance of our attending and MW model to the on-task and zoned-out states of humans as described in the MRT paper. To assess these constraints, we will use a t-test since we possess two groups that we wish to compare on a single measure. We will set the value of α to the commonly accepted value of 0.05.

An unpaired one-tailed t-test revealed that the RRTv of the MW model (M = 8.35, SD = 0.55) compared to the attending model (M = 8.05, SD = 0.68) was significantly higher ($t(139.38) = 2.96$, $p < 0.01$). Thus, our models follow the general pattern of behaviour as observed in the MRT. In addition, an unpaired two-tailed t-test demonstrated that there was no significant difference between the RRTv of the attending model (M = 8.05, SD = 0.68) compared to the humans who were on task (M = 8.01, SD = 0.78), ($t(146) = .33$, $p = .74$). This pattern was also observed for the MW model (M = 8.35, SD = 0.55) compared to humans who were zoned out (M = 8.29, SD = 0.6), ($t(146) = .59$, $p = .56$).

Since all of our constraints have been satisfied, we can claim that our model is capable of modelling human RRTv on the MRT. Thus, we reject the null hypothesis and conclude that the MW implementation of van Vugt et al. (2015) is sufficient for modelling human RRTv on the MRT

Discussion

The current paper sought to determine the robustness of van Vugt et al. (2015)'s theory of MW due to its success with MW in SART. To this end, we wished to determine if this theory could predict human RRTv on the MRT. In order to answer our research question, we created two cognitive models based on the MW theory to simulate human performance while paying attention and MW during the MRT. Our statistical analysis revealed that the RRTv of the MW model was significantly higher than the attending one; a conclusion that was also observed in the empirical data of the MRT paper. In addition, there was no significant difference between the RRTv of our models to their human counterparts. Since our model satisfies all of the constraints of our research question, we can attest to the robustness of van Vugt et al. (2015)'s theory of MW and state that it is sufficient for modelling human RRTv on the MRT.

Quantitative Analysis

As reported in our results, there was no significant difference between our model and human data. However, this is not a true indicator that our model behaves in a similar manner compared to a human. It is possible that our manipulation of parameters would have led to the overfitting of RRTv. We must also take into account that we do not possess a genuine reason for changing the parameters to the specific reported values other than to fit the data. Another factor to consider is that the data for the on-task and zoned-out states in the MRT paper were obtained from the same human. Due to the sake of simplicity, we instead created two different models for comparison with the human data.

Qualitative Analysis

While we cannot assess the correctness of our model's parameters, we can examine the tick threshold of the models at all button presses to determine why we obtained our results. We assumed that the tick threshold of the attending

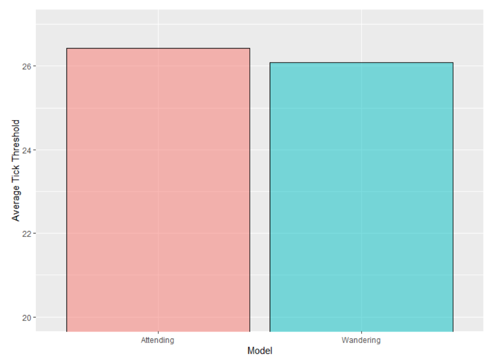

Figure 3: Mean tick threshold of our models. Note that the standard errors are displayed but they are minuscule due to the large sample size of the metronome beats.

model would be closer to the calculated theoretical value of 27 compared to the MW one. Our reasoning behind this is that the attending model spends more time steering itself to the theoretical value. Our analysis of the models' trace file proved that was indeed the case as the attending model (M = 26.43, SD = 0.78) demonstrated a mean tick threshold value that was closer to the theoretical value compared to the MW model (M = 26.09, SD = 0.83). A two-tailed t-test revealed that there was indeed a significant difference between these values, ($t(132678) = 77.07$, $p < 0.01$). This confirmed that our two models demonstrated different behaviour from each other. Thus, the assumption underpinning our model is valid which increases the strength of our claims. Next, we will also assess our model in terms of plausibility, simplicity, and generality to further evaluate our model.

Plausibility: Our model makes use of ACT-R's modules which have been tested through rigorous research. Therefore, the underlying systems of our model are biologically plausible. However, it must be noted that we are not certain about the plausibility of the learning of ticks in our model. We assume that learning of ticks is a gradual process in which an entity slowly steers itself to the optimum value. This might not be a valid assumption as humans can quickly adapt to rhythms as discovered by van Noorden and Moelants (1999). Additionally, an examination of the activation values of the attend and wander states reveal that the model is less likely to mind wander as time goes on. This is contradictory to prior research which harms the plausibility of our model.

Simplicity: It is difficult to assess the simplicity of our model since no other model has been created to simulate human performance on the MRT. Regardless of this fact, we have tried to ensure that the mechanisms in our model are as simple as possible. The biggest difference between both our models is simply the ability to learn the rhythm

Generality: As noted previously, we do not have sound support for the exact changes that we made to our parameters. Thus, we cannot claim that our model would be representative of the average human. Despite this, we can still generate a prediction based on the performance of our model. We noticed that the noisiness of ticks negatively affected the RRTv of the model. If we take into account that this noise would represent the skill in timekeeping, we can arrive at an interesting conclusion. We predict that musicians would demonstrate lower RRTv on the MRT since they possess greater skill with timekeeping. One way to test this would be to gather people with different skill levels of music and make them take the MRT. We could then perform a statistical test to determine the effect of musical experience on RRTv.

Conclusions with Background Literature

The greatest takeaway demonstrated by our model is that the MW theory by van Vugt et al. (2015) is sufficient to explain the RRTv of empirical data in the MRT. Thus, MW can be thought of as the competition between two rival goals: attending and mind wandering. Initially, humans pay attention to the task. However, as time goes on, they get distracted and switch their attention inwards to reminisce memories. In this state, one of the memories reminds the human to pay attention and focus on the task once more.

Using our model, we can also claim that RRTv is a predictor of MW as established by previous research (Seli et al., 2013; Seli, Cheyne, et al., 2015; Seli, Jonker, et al., 2015). As explained in the papers, this effect is apparent as the MRT is a low-demand boring task. Thus, subjects are incentivized to mind wander which negatively impacts performance and serves as an insulation from the negative impact of boredom on mood (Mooneyham & Schooler, 2013). Woefully, our model is not perfect in this regard as we needed to severely reduce the rate of MW to obtain values that are close to human RRTv.

Future Research

As indicated by our example of musicians possessing lower RRTv, it is now possible to generate predictions regarding human performance on the MRT. Testing these could increase our understanding of the cognitive mechanisms of the brain. Despite this triumph, there are a number of ways in which our model can be improved and made more robust.

The data points for paying attention and mind wandering in the MRT were derived from the same human. However, this was something that we circumvented by creating two different models. For the sake of equivalent testing, it is important that a new model is created that simultaneously creates data for both mind-wandering and attending. In addition to this, it would be interesting to implement new mechanisms for learning rhythm which do not gradually steer the model to the optimal tick threshold. Research into this topic might create a new model which does not require parameter optimization to match human performance. Finally, the plausibility of our model can be evaluated using neuro-imaging studies which examine human subjects as they perform the MRT. By observing the activation of brain regions during the task, and then comparing these to the modules that are activated by our model, we will be able to assess whether our model uses the same mechanisms as human subjects.

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