EVALUATION OF THE PROCESSES INVOLVED IN RECOGNITION MEMORY USING STATE-TRACE ANALYSIS OF EVENT-RELATED POTENTIALS

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INTRODUCTION

Episodic recognition memory experiments attempt to determine the processes that underlie recognition (Mandler, 1980). Currently, there is a debate in the literature whether episodic recognition memory involves separate components of familiarity and recollection (i.e., the Dual Process Model) or a single process that involves varying degrees of familiarity based on confidence (i.e., the Single Process Model). In this paper, the validity of the single and dual process models will be assessed by testing the assumptions of the models using electrophysiological data from a recognition experiment. First, background material on the single and dual process models will be reviewed, along with support from behavioral, electrophysiological, and imaging domains. Then, a nonparametric statistical approach used to test the basic assumptions of both classes of models will be described. Lastly, the results from the recognition experiment using this nonparametric statistical technique will be presented.

In typical recognition experiments, participants study a list of items and then are asked to discriminate between studied items (old) and non-studied items (new). This type of test yields two measures: the hit rate, or the amount of old items correctly recognized, and the false alarm rate, or the amount of new items incorrectly identified as old items. By combining the hit rate and false alarm rate, an overall accuracy level of recognition in that context can be formed.

BACKGROUND

The Dual Process Model

The Dual Process theory proposes two separate memory systems and has been supported by much of the past research into recognition memory, especially in the last decade. The Yonelinas (2002) model of the dual process theory is one of the most accepted. It postulates that recognition comprises two separate processes, recollection and familiarity. Recollection and familiarity differ in the type of information they provide and also the extent to which each influences recognition confidence (Yonelinas, Dobbins, Szymanski, Dhaliwal, & King, 1996). Familiarity is specifically assumed to reflect the assessment of quantitative memory strength information. Recollection is believed to reflect a threshold retrieval process whereby qualitative information about a previous event is retrieved (Yonelinas, 2002). Familiarity depends on the amount and the similarity of information in memory store compared to the stimulus. Recollection depends on the type of information in memory store and whether specific qualitative aspects about the stimulus can be remembered. The most important distinction between recollection and familiarity is that familiarity should not support associative memory for two distinct items unless the items can be unitized into a single larger item (Yonelinas 1997, 1999; Yonelinas, Kroll, Dobbins, & Soltani, 1999). This means that familiarity can only be used for rather basic associations, while recollection is effective even for complex learned associations. Recollection is thought to represent relatively high confidence compared to familiarity, which represents a wide range of confidence responses. Much of the evidence supporting the dual process model is based on dissociation logic, which provides evidence that recognition tests based on familiarity are functionally distinct and rely on different neural substrates than those involved in recollection (Jacoby, 1991).

This model states that recollection and familiarity are initiated separately and are independent, parallel processes. (Yonelinas, 2002). The model is supported by the observations that they have distinct electrophysiological correlates and are affected differentially by brain injuries depending on the anatomic location of the damage. Recollection is impaired with hippocampal damage, while familiarity is affected if additional temporal lobe structures are damaged (Yonelinas et al., 1998). These differences, along with the expected differences between learning and confidence suggest recollection and familiarity depend on different neural circuits and are separate processes.

The Single Process Model

Single process models are based on the framework of Signal Detection Theory (SDT) which aims to explain how decisions are made under conditions of uncertainty (Green & Swets, 1967). For example, in SDT, an old or new word in a recognition test is represented by a single continuous latent variable. Participants use response criterion to decide if a word is old or new. If response criterion is above memory strength then people say the word is old. If response criterion is below memory strength people say the word is new (DeCarlo, 2002). There are many variations to the single process model, but most utilize the SDT framework and use a familiarity component which allows one to come to a decision about the perception of the event at hand.

Behavioral, Imaging, and Electrophysiological Evidence

Dual process theorists have used the remember-know paradigm (Tulving, 1985) to add support for two underlying processes in recognition memory. This test requires participants to respond as to whether their 'old' responses are based upon whether they remember (i.e., recollect) or know (i.e., are familiar with) seeing the word in the study list. Joordens & Hockley (2000) and previous studies suggested that the finding that participants are able to distinguish between remembered and known responses is evidence that both recollection and familiarity contribute to recognition. Another finding of this study was that deeper processing at study led to more remembered responses at test while known responses were not affected. Other encoding manipulations such as the generation read and the placebo-benzodiazepine manipulations also express dissociations between recollection and familiarity. The most influential encoding manipulations found to differentially affect recollection and familiarity are shown below in figure 1 (Yonelinas, 2002)

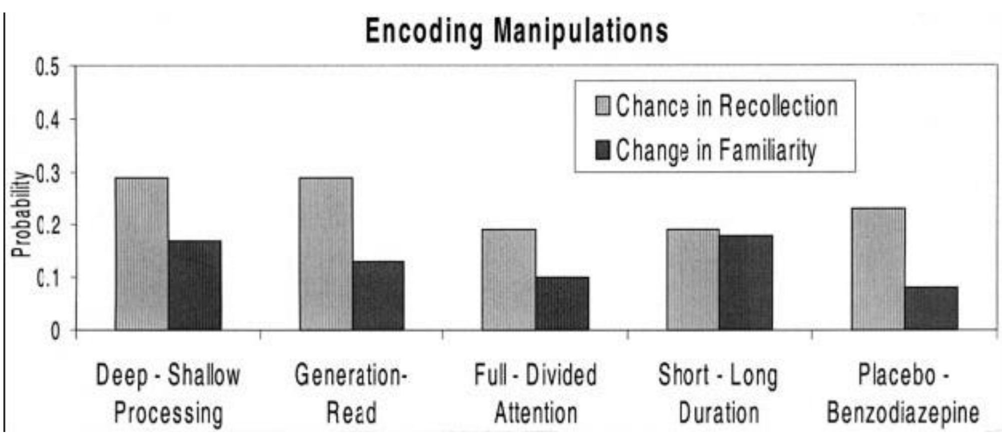


Figure 1: These are the specific encoding manipulations with which dual process theorists have shown recollection and familiarity to differ (Yonelinas, 2002).

Although many dual process theorists have interpreted these dissociations in remember-know tasks as evidence for dual process models, single process theorists have looked at these findings differently. Dunn (2004) conducted a meta-analysis of 72 remember-know studies. He concluded that remember-know responses represent higher or lower levels of confidence respectively and not different underlying processes of recognition. His analysis showed that remember-know data can be fit to a single process signal detection like model, and this model was equally as plausible as a dual process model. This finding has led to increased research involving the neurological basis of recognition in an attempt to determine if there is evidence for distinct biological processes underlying recollection and familiarity.

Yonelinas, Otten, Shaw and Rugg (2005) reported distinct neural signatures for recollection and familiarity. Because past research (Dunn, 2004) suggested that remember responses simply reflect a participant's high level of confidence, and not recollection, Yonelinas et al. had their participants respond 'remember' if they could remember something specific about the study episode. If they could not remember something specific about the study episode they were asked to give a confidence rating that the item was studied using a four-point scale on how sure they were that the word was old or new. They found that there were different neural signatures for remember and high confidence familiar responses. This finding led to the conclusion that recollection and familiarity are two distinct processes.

Curran (1999, 2004) assessed event-related potentials (ERPs) associated with recollection and familiarity. He focused on two time periods, 300-500ms and 400-800ms after stimulus presentation, which represent the frontal negative peak at 400ms (FN400) and late parietal component (LPC). Curran has argued that the FN400 is related to familiarity while the LPC is related to recollection based on the finding that in remember-know studies studied items produce a more negative FN400 than unstudied items and remembered items produce a more positive LPC than known items. However, Finnigan, Humphreys, Dennis, & Geffen (2002) showed that these findings are consistent with a single process model where the FN400 represents strength of recognition and the LPC represents confidence.

There is continuing debate as to the validity of these findings especially concerning those based on dissociation logic, which has been shown by Dunn and Kirsner (2002) to be an invalid method of interpreting recognition and potentially cognition itself. Dissociation logic is the idea that an independent variable (IV) that differentially affects a dependent variable (DV) is evidence of multiple processes. However, many of these studies compared a physical variable (e.g., scalp voltages) with a psychological variable (e.g., memory strength). It was assumed that these variables were related linearly so differences in DV scores were viewed as dissociations. Assuming that corresponding psychological and physical variables must be linearly related seems overly restrictive. Our goal is to evaluate our findings described below without using dissociation logic.

State-Trace Analysis

State-trace is a nonparametric method that looks to determine the number of underlying processes that are needed to account for a given set of data without making prior assumptions of a single or dual process model. It is a general method based on the premise that two DVs will covary with each other to the extent that they are affected by the same IV (Bamber, 1979). This method is most effectively used in pre-model building to frame the process of interest.

The results from a state-trace experiment are presented in a state-trace plot, a graphical representation of the data collected in the state-trace analysis. This plot can either be unidimensional or bidimensional. In a unidimensional state-trace model, the effect of the IV on the DVs is mediated by one intervening variable. When the data for a unidimensional state-trace are plotted, the points from both DVs forms a single function. To the eye it would look as if both sets of data formed a single line or curve (see Figure 2). In a bidimensional model, the factor (IV) effect is mediated by two or more intervening variables (Dunn, 2008). Instead of a single function and resulting curve or line, the data sets create two distinct functions. Therefore, two distinct curves or lines are generated. With respect to recognition, this would mean that two factors, such as familiarity and recollection are responsible for recognition responses. State-trace treats these intervening variables as separate entities or parts, for example, they could be separate memory system, structures, etc.

Unidimensional state-trace   Bidimensional state-trace

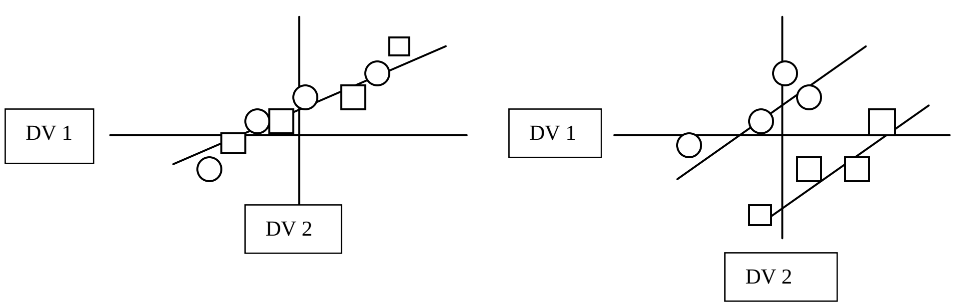


Figure 2: These graphs show the difference between a unidimensional and bidimensional state trace. In an unidimensional state-trace the data from both dependent variables forms a single function. This would be produced if a single process is involved in recognition. A bidimensional state-trace the dependent variables create two separate functions. This supports a dual process in recognition memory.

The state trace plot in this recognition experiment contains three factors: state, dimensional, and trace, which are representative of the DVs and IVs. The state factor is the ERP readings for each level of the IVs. The dimension factor is represented by the divided vs. focused attention condition. The dimension factor represents what is supposed to differ between recollection and familiarity (Yonelinas, 2002). Lastly, the plot employs a trace factor. This factor must have a monotonic effect on the dimension factor. In other words it affects the levels of the dimension factor equally (Heathcote, unpublished). The trace factor for our experiment, number of repetitions, has been shown in previous studies to monotonically effect accuracy in recognition experiments (Bamber, 1979; Hintzman, 2004; Jang & Nelson, 2005). The trace factor should be manipulated in order to maximize overlap between the dimension factors. This is done to compensate for the effect of the dimension manipulation (Heathcote, unpublished).

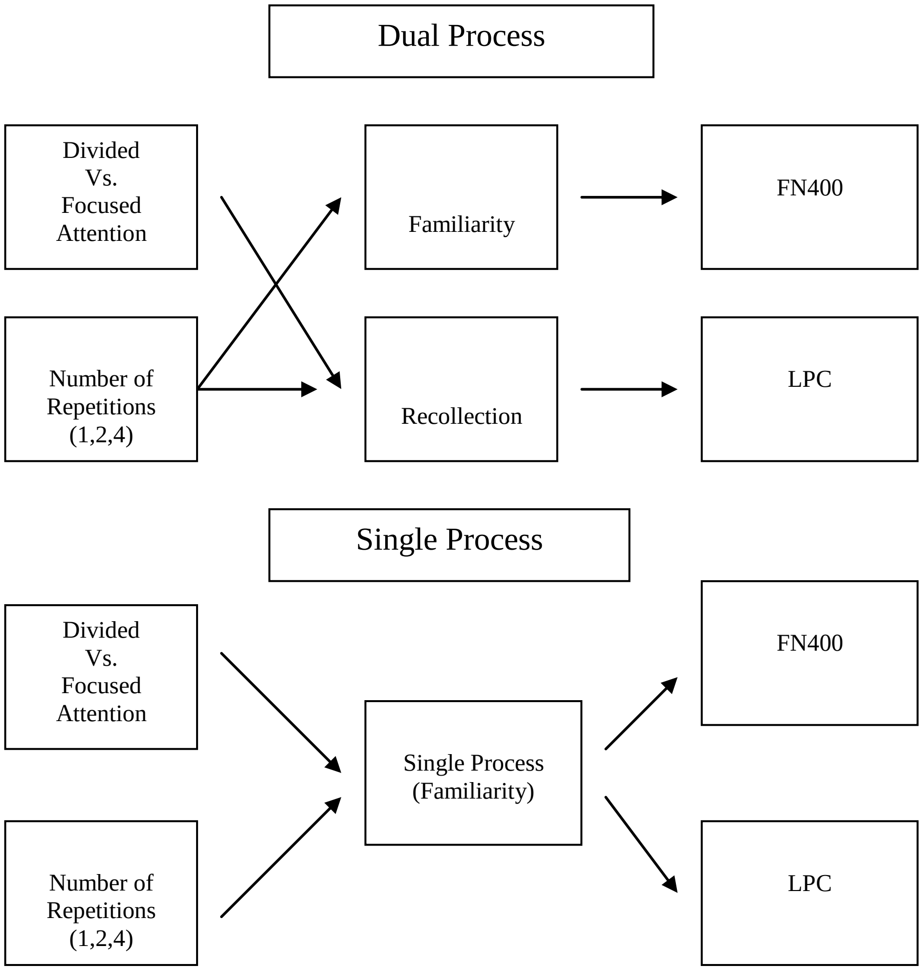


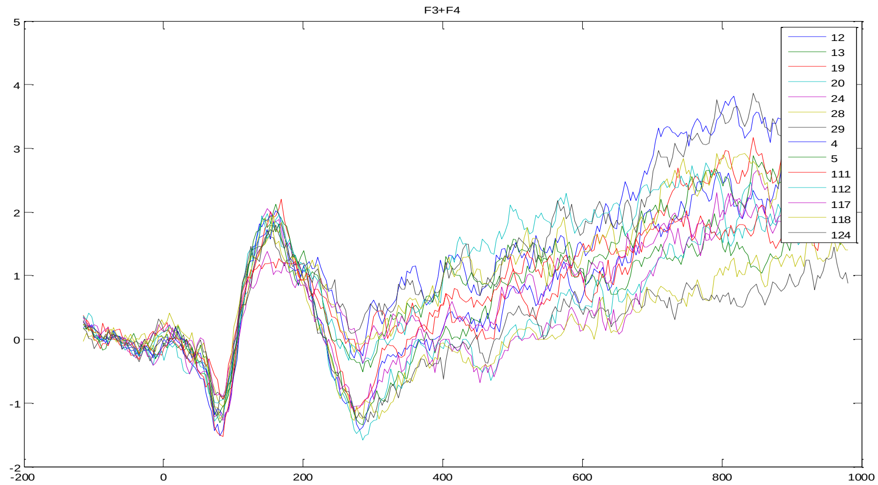
Figure 3: This diagram depicts the relationship between the independent variables, divided/focused attention and number of repetitions, and their affects on the dependent variable. The first diagram is of a dual process model. The dimension variable, divided vs. focused attention differentially affects recollection. The trace variable, number of repetitions, shouldn't affect recollection and familiarity differentially and is used to trace the difference that should be caused from the divided vs. focused attention manipulation. The state variables are the ERP readings that result from the recognition task. Values obtained for the six attention by repetition conditions are plotted over the state variables to produce the state-trace plot. The second diagram depicts a single process model where neither variable differentially affects the resulting dependent variables. The state, dimension and trace variables are the same.

State-trace analysis has two main advantages over typical model building. First, state trace allows for entire classes of models to be tested under very general conditions, which makes the technique easier to use than traditional model building and increases the likelihood that the simplest model is created. Second, it directly forecasts the different dimensionalities of the models under consideration, a feature that is not always apparent in direct model-fitting approaches (Dunn, 2008). State-trace shows how many dimensions underlie a model, making the model building process more efficient. In this project, I utilized state-trace analysis to evaluate how many processes are apparent from the data collected from a recognition test. The state-trace analysis was expected to show that two dimensions underlie the model of recognition memory (recollection and familiarity) or that only one dimension underlies it (familiarity).

Event-Related Potentials

Event-related potentials (ERPs) are EEG voltage potentials recorded from the scalp that are time-locked to a stimulus or task. ERPs are useful in locating brain activities for specific functions and determining latency of action. Curran & Cleary (2003) provided evidence that ERPs can be used to dissociate different mechanisms in recognition memory, including recollection and familiarity. They hypothesized that the FN400 old/new effect (300-500ms) varies with familiarity and the LPC (400-800ms) varies with recollection (Curran & Cleary, 2003). Refer to figure 4 for a depiction and description of the FN400 and the LPC.

FN400



LPC

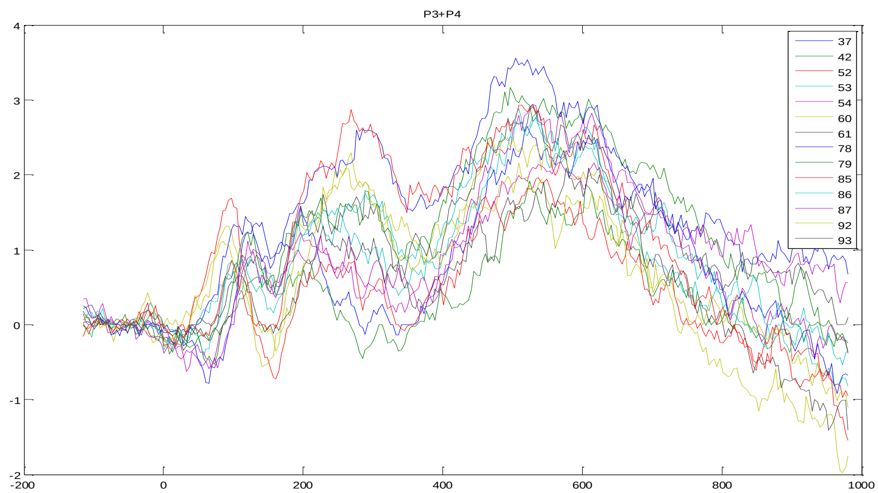


Figure 4: Looking at the frontal waveform or FN400 we see a dip in the waveform between 300-500ms. Looking at the parietal or LPC waveform we see a spike between 500-800ms. These represent familiarity and recollection respectively as shown by Curran & Cleary (2003).

In this project, ERPs were measured during a recognition task and analyzed by state-trace. By examining the FN400 and LPC waveforms and how they interact with the

IVs, the goal was to determine whether recognition is best modeled by a single or dual process.

SIGNIFICANCE

This project aims to provide evidence in support of a single process model of recognition memory. This will expand our understanding of recognition memory and also the use of the state-trace technique as a tool to enhance model building. It was hypothesized that a state-trace analysis of the recognition would yield a monotonic curve revealing recognition memory to best be modeled by a single process model. An additional aim of this project was to gain a better understanding of analytic techniques that can be applied to ERP data, which will be useful for future studies with this technology.

MATERIALS and METHODS

Study population: The study participants were 46 undergraduate students taking part in the Psychology 100 REP program (where psychology 100 student receive credit for participation in experiments).

Materials: The stimuli used were 240 high frequency words, with a mean frequency of 155 (ratings taken from the Celex database, Baayen, Piepenbrock, & van Rijn, 1993). All words were 4-8 letters long with a mean length of 4.6 letters. Words were divided into 6 separate lists for each participant. All items were randomly allocated to old/new, focused/divided attention, and repetition conditions.

Design: The experiment utilized a 2x3 design, with attention at study (focused/divided) and number of study presentations (1/2/4) manipulated within-participants.

Procedure: Participants were briefed about the experiment, signed a consent form, and were then fitted with an EEG head net.

In each study list there were 24 words. Half the words were presented alone on the screen (focused condition) while the other half were presented with numbers on either side of the word (divided condition). In the divided attention condition, the numbers appeared for 200 ms then were covered. The numbers differed in both physical size and numerical value. After the target word was removed from the screen, participants were asked to report, depending on the cue given, if the number on the right or the left was larger in either value or size. One third of stimuli were presented once, one third were presented twice, and one third were presented four times, giving the study phase a total of 56 trials. Also, repeated words were always repeated within the same attention condition. Words were presented for three seconds followed by a one second interstimulus interval.

Following each study phase, participants completed three math problems for which they were given one minute to complete each problem. Their answers were reported to the experimenter.

The test list consisted of 48 words, 24 new (not seen in study) and 24 old (seen in study). Each word was presented for two seconds followed by a response cue. At this time the participant was required to respond whether the word was old or new and provide a confidence rating on their answer. There were three levels of confidence, ranging from highly confident to slightly confident. Participants were told to wait for the cue before responding, stay as still as possible, and minimize eye blinks.

Each study/test cycle took about 15 minutes. After each cycle, the electrode net impedances were checked to ensure they stayed below 50 kohm. Participants completed an average of six study/test cycles within a 2.5 hour period.

EEG Recordings: Scalp voltages were collected using 128 Electro Geodesics Sensor Net connected to a high impedance amplifier (300 kohm Net Amps, Electrical Geodesics Inc, Eugene, OR, USA). Amplified analog voltages (0.1-100Hz bandpass, -3dB) were digitized at 500Hz. Individual sensors were adjusted until each reached an impedance of less than 50 kohm. The EEG was digitally low pass filtered at 40Hz.

RESULTS

A total of 46 participants were recruited for this experiment from the Psychology 100 Research Education Program (REP). They were college age, 18-24, with about half of the participants being male, the other half female. Approximately 120 participants were tested, but there was a high discard rate due to technical and experimental difficulties. Trials were discarded from the analysis if they contained eye movements (EOG over 70μV), or more than 20% of channels were bad (average amplitude over 200 μV or transit amplitude over 100ms). Individual bad channels were replaced on a trial by trial basis with a spherical spline algorithm (Srinivasan, Nunez, Silberstein, Tucker, & Cadusch, 1996). Consistently bad channels for a given participant were replaced throughout the participant's entire dataset. EEG's were measured with respect to a vertex reference (Cz), but an average-reference transformation was used to minimize the effects of reference-site activity and accurately estimate the scalp topography of the measured electrical fields (Dien, 1998; Picton, Lins, & Scherg, 1995).

Average-reference ERPs were computed for each channel as the voltage difference between that channel and the average of all channels. The average reference was corrected for polar average reference effect (Junghofer, Elbert, Tucker, & Braun, 1999). ERPs were baseline-corrected with respect to a 100ms prestimulus recording interval.

Figure 5 summarizes the behavioral results for this experiment. As expected, recognition scores for the focused attention condition are higher than those for the divided attention condition. There is very little variability in the behavioral data as shown by the small error bars.

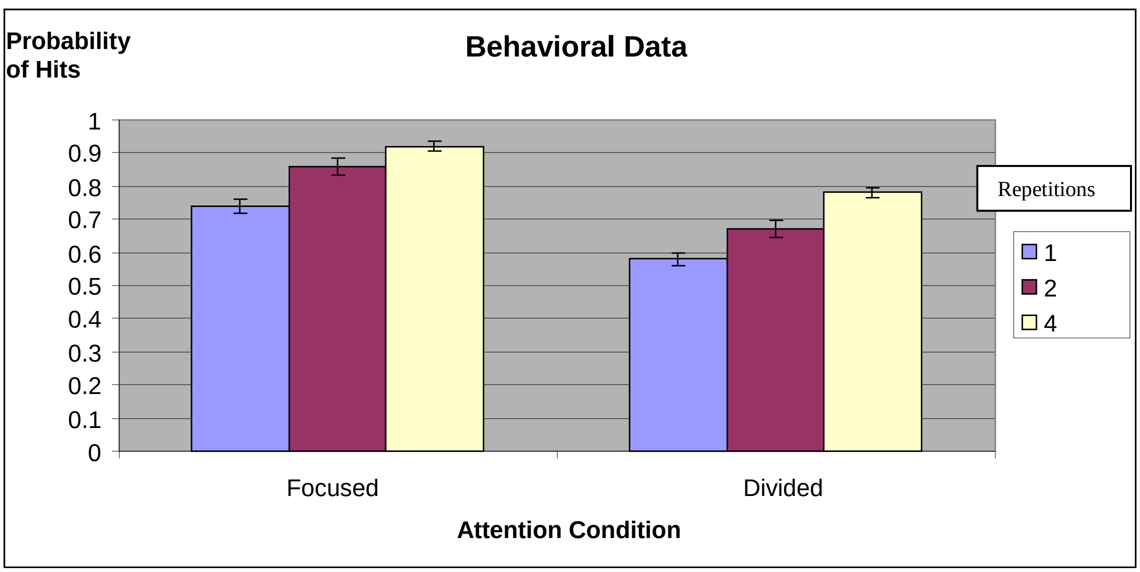


Figure 5: This graph shows the hit rates for this recognition experiment. The recognition scores are higher for the focused attention condition as expected. The false alarm rate for the experiment was .29 with a standard error of .02.

As expected the attention factor is significant, ($F(1,90) = 71.258$, $P < 0.01$). The repetition factor was also significant, ($F(2,90) = 97.652$, $P < 0.01$).

Figure 6 shows the state-trace plot for median LPC voltages (x-axis) vs. median FN400 voltages (y-axis) under the six attention vs. repetition conditions. The star on the plot is the reading taken during the distracter phase. This is used as a baseline measure to which the other conditions are compared. The median voltage readings for the LPC and FN400 are used to plot the 6 conditions; focused 1, focused 2, focused 3, divided 1, divided 2, divided 3. The curve created increases with increased study for both divided and focused attention. Also, there is a large overlap between the two conditions and the 95% confidence intervals which leads to the assumption of little difference between the two conditions.

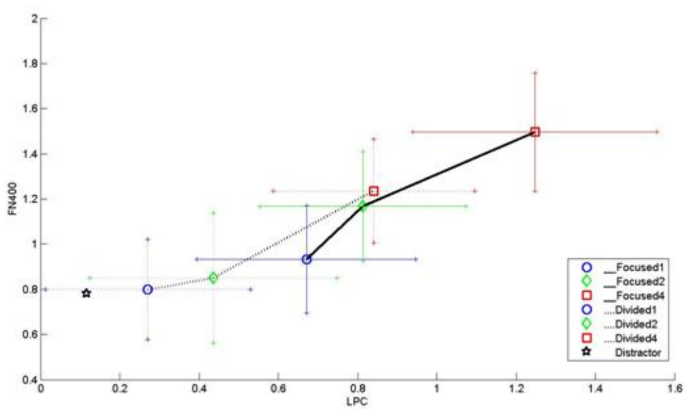


Figure 6: State-trace plot of the ERP results showing the median LPC plotted as a function of the median FN400 for each of the attention by repetition condition.

DISCUSSION

The underlying processes involved in recognition have been a much debated topic in cognitive psychology for the last few decades. Two sides dominate the discussion, those in favor of a dual process and those in favor of a single process. The dual process model is explained using recollection and familiarity as its two components. Recollection is a context dependent memory process and is associated with high confidence responses. Familiarity is a context independent memory process and can be associated with differing levels of confidence. The single process model is explained using a single memory process.

The goal of this project was to perform an evaluation of the number of underlying processes in recognition memory using state-trace analysis of ERPs collected during a divided/focused attention task. State-trace was chosen over traditional statistical methods because it is not confined to the use of dissociation logic. State-trace also allows for easier, unbiased model building.

The state-trace plot of our data is clearly monotonic and, therefore, supports a single process model of recognition memory. While this observation does not yield specific information about how this single process model works, it provides a starting point for researchers to test and fit a model to the process of recognition. This is important because a general idea of how recognition works (the number of processes) enables the model fitting process to run more smoothly and helps to ensure that a more parsimonious model is created.

We can also infer from the plot that if the divided attention task had been made easier there would have been more overlap between the two curves. This is expected because an easier task would lead to more correct answers in the divided attention aspect of this manipulation than a more difficult task. This would decrease the difference between score in the focused task with those in the divided task which in turn would create more overlap in the plot. Creating more overlap is important because it provides more evidence for a single process model and helps to rule out a dual process model.

Dunn and Kirsner's (2003) findings on double dissociations are also supported by the results of this study. The double dissociation of the FN400 and LPC ERPs proposed by Curran and Cleary (2000, 2004), does not imply two distinct processes. The problem with these studies is that they assumed that changes in ERP amplitude (a physical variable) and memory strength (a psychological variable) are linearly related. This assumption led the researchers to believe that differences in ERP reading implied different components of recognition. Our use of state-trace illustrated that this belief is incorrect.

It had been suggested by Yonelinas (2002) that dividing attention during study would result in different scores for recollection at test. The idea was that items in the focused attention condition would have higher recollection scores than items in the divided attention condition. Using state-trace, Dunn, Heathcote, Dennis, and deZubicary (in preparation) were able to illustrate that a single monotonic curve could be created from an experiment in which attention was manipulated. Our findings come to the same conclusion and add support to the findings of Dunn et. Al.

Due to experimental constraints, the study population was limited to college students. This sample may not be an accurate portrayal of a more general population. Also, there was also a high discard rate for participant's trials. However these two issues do not invalidate the results from this experiment. The results explain the process of recognition for college age people. These findings can be extrapolated to represent a more general population. Secondly, participants or trials were not discarded based on performance of the cognitive task. Rather, participants were discarded only if their ERP signals could not properly be read or the noise to signal ratio was too large. Exclusion of these subjects would not be expected to systematically bias the results.

The results for this experiment could be made more definitive by making a few changes to the experimental design. One issue with the results is that the confidence intervals of each point on the state-trace plot are large. The size of these intervals allows the possibility of more than one process. However a dual process was not found to be statistically significant. The confidence intervals for both ERP measures could have been decreased by increased sample size. Improved methodology of ERP testing could have decreased technical variability in that variable.

Similarly, performance of the cognitive task showed substantial variability. The discrepancies between scores are most likely related to differing levels of attention and motivation during the experiment by individual participants. Also, participants exhibited differing patterns of responses, i.e. differing proportions of misses, false alarms, correct rejections, and hits, suggesting different strategies for performing the task. Finally, factors such as gender, time of day, day of the week, prior testing experience, etc., which conceivably could have affected test performance, were not taken into account in the experimental design.

This study opens the door for increased use of state-trace analysis in model building process for many cognitive functions. The ability of state-trace to directly forecast the amount of underlying processes involved in cognitive function will specifically improve model building providing the most parsimonious framework with which to build a model. It will also provide a means to test current models of cognition in an unbiased fashion.

Future studies to further validate these results could include functional magnetic resonance imaging (fMRI) during a remember-know test paradigm to assess whether similar or distinct brain regions are activated. Finding support for a single process using fMRI would provide clear and strong support for a single process in behavioral, electrophysiological, and imaging domains. These findings would have a profound impact on and change the way cognition is believed to function and how it is tested.

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