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A diffusion model analysis of the effects of aging on recognition memory☆

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Abstract

The effects of aging on response time were examined in a recognition memory experiment with young, college age subjects and older, 60–75 year old subjects. The older subjects were slower than the young subjects but almost as accurate. Ratcliff's (1978) diffusion model was fit to the data and it provided a good account of response times, their distributions, and accuracy values. The fits showed a 100 ms slowing of the nondecision components of response time for older subjects relative to young subjects, and roughly equal response criteria settings with accuracy instructions but more conservative settings for the older subjects with speed instructions. In the diffusion model, the decision process is driven by the rate of accumulation of evidence from the stimulus. We found that the rate of accumulation for older subjects was a non-significant 7% lower than the rate for young subjects, indicating that the output from recognition memory entering the decision process was not significantly worse for the older subjects. The results are compared to those obtained from letter discrimination, brightness discrimination, and signal detection-like tasks.

Keywords: Diffusion; Recognition; Aging; Response time; Speed–accuracy

A central finding in the literature on aging is that as people age, their response times increase. Along with the increase in response times, performance sometimes shows a decrease in accuracy. Recently, Ratcliff, Thapar, and McKoon (2001, 2003) and Thapar, Ratcliff, and McKoon (2003) examined the effects of aging on performance in several two-choice tasks: signal detection-like tasks, a brightness discrimination task, and a letter discrimination task. By applying the diffusion model (Ratcliff, 1978, 1981, 1985, 1988; Ratcliff & Rouder, 1998, 2000; Ratcliff, Van Zandt, & McKoon, 1999) to the data, they were able to separate out the effects of aging on several components of processing in the model. The older subjects in their studies adopted more conservative decision criteria than the young subjects and they were also slower in components of processing outside the decision itself (e.g., encoding and response execution). In some tasks, the quality of the stimulus evidence driving the decision process was not significantly lower for the older subjects than the young ones, although in other tasks, it showed a deficit. For the brightness and letter discrimination tasks, the deficits occurred exactly as would be predicted from psychophysical research on the effects of aging on visual discrimination (Coyne, 1981; Fozard, 1990; Owsley, Sekuler, & Siemsen, 1983; Spear, 1993): a deficit occurred with the high spatial frequencies in letters in the letter discrimination task but not with the low spatial frequencies of the stimuli in the brightness discrimination task.

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Not only does the diffusion model allow the response time and accuracy data from a two-choice task to be analyzed in terms of the components of processing required by the task, it also has an advantage over other approaches because it deals with all the aspects of the data: correct and error response times and their relative speeds, the shapes of response time distributions for both correct and error responses, and accuracy values. The model has been successful in accounting for the data from a variety of two-choice response time tasks and a variety of task manipulations (Ratcliff, 1978, 1981, 1988, 2002; Ratcliff, Gomez, & McKoon, in press; Ratcliff & Rouder, 1998, 2000; Ratcliff et al., 2001, 2003; Ratcliff et al., 1999; Thapar et al., 2003). In this article, the diffusion model is applied to examine the effects of aging on recognition memory.

Previously, the main conclusion in the literature has been that aging has little effect on recognition memory; data show no effect at all or only a small effect (Balota, Dolan, & Duchek, 2000; Bowles & Poon, 1982; Craik, 1994; Craik & Jennings, 1992; Erber, 1974; Gordon & Clark, 1974; Kausler, 1994; Naveh-Benjamin, 2000; Neath, 1998, Chap. 16; Rabinowitz, 1984; Schonfield & Robertson, 1966). However, the studies from which these conclusions are drawn have measured only recognition accuracy, not response time. As mentioned above, older adults are typically slower, often much slower, than young adults on cognitive tasks. This presents a puzzle: slowing for older adults has often been interpreted as a deficit such that, for example, cognitive operations are not fully completed in the available time and the products of earlier operations are not fully available for later operations (e.g., Salthouse, 1996). In this context, the findings that older adults show no deficit in recognition memory relative to young subjects are surprising.

The experiment presented here measured both accuracy and response time. Simultaneously accounting for both measures, the diffusion model allows the separation of components of processing. In particular, the aim was to determine whether older adults are slower than young adults and if so, to determine whether the slowing reflects a deficit in the quality of information available from memory or increased processing time for some other, non-memory, components of processing.

In the experiment, the number of repetitions of the words to be learned and word frequency were manipulated. With these two variables, accuracy can be varied from high to moderately low. Sweeping out response times over a wide range of accuracy values provides maximal constraints on fitting the diffusion model to data (Ratcliff & Tuerlinckx, 2002). We also manipulated speed–accuracy criteria to provide additional constraints on the model. For some trials, subjects were instructed to respond as quickly as possible, and on other trials, as accurately as possible. The overall aim was to allow the effects of aging on response time and accuracy to be examined in a unified framework, separating out the quality of the memory information entering the decision process from the speed–accuracy decision criteria adopted by subjects and from non-decision components of processing.

The diffusion model

The diffusion model is a model of the cognitive processes involved in making simple two-choice decisions. It separates the quality of evidence entering the decision from the decision criteria and from other, non-decision processes such as encoding the stimulus and response execution. The model applies only to relatively fast two-choice decisions (mean response times less than about 1000–1500 ms) and only to decisions that are a single-stage decision process (as opposed to the multiple-stage processes that might be involved in, for example, reasoning tasks or card sorting tasks). Other models in the class of diffusion models have been applied to decision making (Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001) and simple reaction time (Smith, 1995). For a detailed comparison of the sequential sampling models, see Ratcliff and Smith (in press).

The diffusion model assumes that decisions are made by a noisy process that accumulates information over time from a starting point toward one of two response criteria or boundaries, as in Fig. 1, where the starting point is labeled z and the boundaries are labeled a and 0. When one of the boundaries is reached, a response is initiated. The rate of accumulation of information is

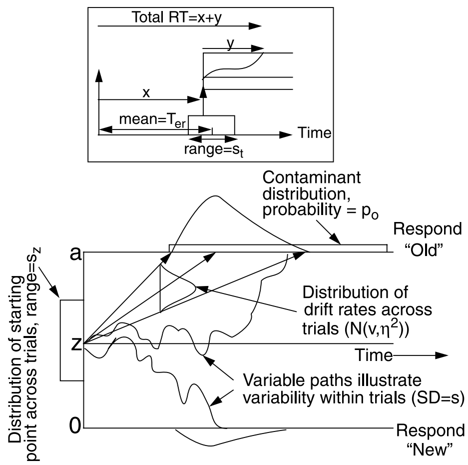

Fig. 1. An illustration of the diffusion model. Parameters of the model are: a, boundary separation; z, starting point; T_{er}, mean value of the non-decision component of response time; η, SD in drift across trials; s_z, range of the distribution of starting point (z) across trials; v, drift rate; p_0, proportion of contaminants; s_t, range of the distribution of non-decision times across trials; and s, SD in variability in drift within trials.