Modeling a Visual Search Task with a Secondary Task in IMPRINT

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1. Introduction

IMPRINT is an Army modeling tool used to simulate complex, long-term activities involving personnel and equipment. Recently, it was used to model a simple psychomotor task, digit data entry (Buck-Gengler, Raymond, Healy, & Bourne, 2007). In parallel with ACT-R modeling efforts (Best, Gonzalez, Young, Healy, & Bourne, 2007), the work reported here involves IMPRINT modeling of a visual search task (RADAR) coupled with an auditory secondary task. The ACT-R and IMPRINT models are part of a larger research program aimed at understanding the effects of training on performance. The RADAR model implements the effects on performance, during training and delayed test, of several training manipulations, allowing investigation of the consequences of varying training parameters through simulation.

2. Experimental basis of the model

The RADAR task was developed by Gonzalez and Thomas (2008). In the experiment modeled here (Young, Healy, Gonzalez, & Bourne, 2007), subjects searched for symbol targets in 4 squares moving from the 4 corners to the center of a radar-like display in 2.062 s. Different sets of symbols were shown in each of 7 frames comprising a trial. Squares did not always contain a symbol. Subjects were to respond only if a target appeared, and were scored on response speed and accuracy.

The experiment contained both consistent mapping (CM) and variable mapping (VM) trials. In CM targets and foils came from different symbol types (letters, digits), so could be distinguished by set membership alone; in VM both targets and foils were from the same set, requiring specific memory for target items. Processing load was manipulated by varying memory load and search difficulty. In low processing load trials (LP) the target set consisted of a single symbol and only 1 square contained a symbol, with the rest being blank. In high processing load trials (HP) the target set consisted of 4 symbols and all 4 squares contained a symbol, although only at most 1 symbol was from the target set.

Trials were grouped in blocks of 20, with 8 blocks in each of 2 sessions. Session 1 (training) occurred 1 week before Session 2 (test). A random 15 of the 20 trials in each block contained a target. All trials in a block had the same mapping type and processing load, and the block type varied systematically across the 8 blocks in the following order: CM1, CM4, VM1, VM4, VM4, VM1, CM4, CM1 (where 1 indicates LP and 4 indicates HP).

The effects on the main task of a concurrent secondary task, namely, counting and reporting the number of tones heard during a trial that deviated from a standard (base) tone, were also examined. In tone-counting conditions tones were played throughout the experiment, 500-1500 ms apart. About 15% of the tones deviated obviously from the base tone. There were 48 subjects; half trained with tone counting and target detection and half performed target detection in silence. At test, half the subjects in each tone condition stayed in the same condition and half switched to the other tone condition.

For the primary task of target detection, correct response times (RTs) were faster overall for CM than for VM, and also for LP than for HP. The disadvantage for HP was larger overall for VM than for CM; this interaction was evident at both training and test. Accuracy in terms of hit rate (HR) also showed an interaction; HR was lowest for the VM4 trials. The results for false alarm rate (FAR) were more complex and demonstrated improvement across trials as well as effects of mapping type and processing load.

Tone counting negatively impacted all measures in both sessions. Furthermore, counter-intuitively, training with tone resulted in reduced speed and accuracy in both tone conditions at test.

3. Model

The cognitive model of the visual search task simulated in IMPRINT consists of three processing subtasks: (1) eye movement to a square containing a symbol, (2) decision as to whether that square contains a target, and (3) manual response when a target is detected. Subtasks are repeated until the target is found, all squares have been searched, or the trial times out.

Implementation details of the eye movement subtasks differed depending on processing load; details of decision subtasks differed depending on mapping type and training condition. Eye movements in the LP conditions were to the square containing a symbol; in the HP conditions any square could be moved to first, resulting in shorter movement time, with equivalent times for subsequent movements. In CM, whether the square with a symbol contains a target can be decided simply by comparing the target's symbol type to the symbol type of a square's content. In VM, target decisions require comparison of the square's content to the target set in memory. In VM1, the decision is a comparison of the single target with the square's content, with decision time equivalent to that for CM. In VM4, 4 possible targets must be compared against each square examined, resulting in longer decision times. In all trials, if a target is detected, a response is made and the trial ends; otherwise, the condition-appropriate subtasks repeat until a target has been detected or all 7 trial frames have been presented.

The IMPRINT model was implemented as two parallel networks: one network represented the computer presenting the visual stimuli (and tones, in those conditions); a separate network represented the subject processing stimuli as they were presented.

Hits were modeled stochastically for frames with targets. HR was lower for VM4 trials than other trial types. False alarms were also modeled stochastically for frames without targets. The FAR declines were implemented with exponential functions across trials, with exponents determined by block type. Initial rates in a block were based on the FAR at the end of the previous block and the type of change in difficulty from the previous block to the current block.

RTs for frames with hits were the sum of eye movement, decision, and response times. Eye movement and response times were based on IMPRINT micromodels for eye movement and key pressing. CM and VM1 decision times were modeled stochastically. Greater VM4 decision times were multiples of VM1 times to model search of the memory set. RTs were increased and HRs were decreased to simulate the additional load of the secondary task and the impairment at test from training with tone counting.

4. Results and conclusion

The empirical data were used informally to derive reasonable parameter values, but it was not practical to optimize all values. The final model was used to simulate the experimental data twice, with two different seeds to produce different statistical subject populations. For each simulation the model was executed with 48 statistical subjects, 12 in each tone counting × session condition. The model's goodness of fit was evaluated by computing r^2 and RMSE values on the block means produced by the two runs of the model and comparing those with each other and with the experimental data from Young et al. (2007) for each measure. The model fit the experimental data well for RT (r^2 (30) = .975) and HR (r^2 (30) = .969), but less well for FAR (r^2 (62) = .461); however, the comparisons for FAR had twice as many data points to fit, and the experimental data were not as regular.

The modeling effort was valuable because it revealed that learning within a session on the RADAR task only occurred for the FAR measure. The critical aspect of this model with respect to broader issues concerning training a complex skill is the ability to reproduce both the immediate effects of a secondary task and the counterintuitive finding that training with a secondary task hurt rather than helped subsequent test performance, even when training and testing conditions matched.

5. References

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