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Divided Attention in Computer Game Play: Analysis Utilizing Unobtrusive Health Monitoring

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Abstract—**Divided attention is a vital cognitive ability used in important daily activities (e.g., driving), which tends to deteriorate with age. As with Alzheimer's and other neural degenerative conditions, treatment for divided attention problems is likely to be more effective the earlier it is detected. Thus, it is important that a method be found to detect changes in divided attention early on in the process, for both safety and health care reasons. We present here a new method for detecting divided attention unobtrusively, using performance on a computer game designed to force players to attend to different dimensions simultaneously in order to succeed. Should this model prove to predict scores on a standard test for divided attention, it could help to detect cognitive decline earlier in our increasingly computer-involved aging population, providing treatment efficacy benefits to those who will experience cognitive decline.**

I. Introduction

TESTS for the cognitive decline associated with Alzheimer's disease (AD) and mild cognitive impairment (MCI) are often too coarse to identify the disease within an ideal amount of time [1]. Indeed, very often such tests are superfluous; by the time a patient has declined enough to receive a low score on a standard cognitive screening test, the result is often merely a confirmation of what friends and family members have known for some time. This is especially tragic given that most drugs that are used to treat cognitive decline can only slow the process, not reverse it. This makes it especially important that these diseases be caught in their earliest possible stages.

One obstacle to identification of early stage AD is the necessity that the patient visit a clinician in order to be tested. This may seem natural, but when testing for cognitive decline it presents several serious difficulties. One of the hallmarks of early-stage AD is increased variability in emotion, motor control, and cognition [2]; on the day of the test, someone suffering from the disease is more likely to have an unusually good (or bad) day, confounding the diagnosis for at least six months. Additionally, the act of visiting a neurologist removes the patient from their normal environment, heightening their stress and attention levels and causing the results to be even more variable. Finally, a diagnosis of AD or MCI is an extremely serious issue, arguably even worse than other terminal diseases due to our cultural stigma regarding the loss of mental ability. This gives patients extremely strong motivation to do well on the tests, to "prove" that they are cognitively intact – even if they know that they are suffering some deficits.

All of these factors can be addressed by having a continuous cognitive monitoring system in place which records a baseline of activity when the patient is cognitively proficient and stable, and then compares the current state to that baseline to determine both absolute decrease and variability over time (both indicators of early-stage decline). Ideally, this system would be unobtrusive and could gather information correlated to neurological test scores from data collected during the patient's normal daily routine.

One typical daily activity from which information may be gleaned is computer use. Many elderly people currently use computers for multiple hours per day, on average, and this number is growing exponentially. Soon this will be one of the primary pastimes for Americans over the age of 65 [3].

One particularly rich computer environment from which to glean information about a person's cognitive state is computer game play. Typically, a computer game will emphasize at least one aspect of cognition (planning, executive function, reflexes, memory, etc.) which, is one factor used to determine the outcome or score [4].

This study examined scores from a game which emphasizes divided attention, a skill associated with driving and other normal daily activities [5]. We attempt to show that participants who have more difficulty dividing their attention, or who are more variable in their emphasis on divided attention, do worse at the game. If this is true, then score on this game could be used as one micromeasurement within a larger, unobtrusively-obtained, composite picture of cognitive health.

II. Methods

A. Study

Development and deployment of the software, recruitment of participants, and neurological testing were all performed as described previously [6]. Briefly, the computer game used in the analysis, "21 Tally," was developed along with several other games as a result of previous studies of aspects of gameplay contributing to cognition combined with focus

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group data regarding playability and game enjoyment. 21 Tally was specifically developed to target divided attention as described below. Thirty elderly participants were recruited for a 3-month and then a 1-year study in which they agreed to play the games at least once a week, but several of them found the game so appealing that they chose to play it more than any other game.

The cognitive state of each participant was assessed by a battery of neurological tests given at the beginning and end of the study. Tests performed included *verbal fluency, word list acquisition, word list recognition, constructional praxis, trail-making test, symbol digit modalities test, letter-number sequencing,* and *finger tap test*. Although some of these tests implicitly evaluate executive function and attention, pen-and-paper tests typically do not directly address divided attention.

B. Computer-Based Game Description

21 Tally can be thought of as blackjack played in two dimensions. There are sixteen spaces on the board which can accept cards, arranged in a 4x4 grid (Fig. 1). A player draws cards randomly from the deck (at a fixed probability of 1/52 for each card) and then places the card into an open spot.

Fig. 1. A typical 21 Tally game board, after 2 moves have been made. The empty spaces have been marked with numbers (not visible to the player) showing the equivalence and contingency table placement of each of the possible moves. Moves marked “1” are ideal in both row and column; “2” are ideal in column but not row; “3” are ideal in row but not column; “4” are ideal in neither.

If the player creates a row or a column that have values summing to 21 (facecards are worth 10, Aces are worth 1 or 11), then they have made a win and receive points. Making a certain number of wins (increasing as level increases) will allow the player to advance to the next level. If they make a row or column which sums to greater than 21, then they have made a bust. Making a certain number of busts (decreasing as level increases) will cause the player to lose the game. Note that making a tally or bust on both a row and a column (or a tally on one and a bust on the other) is possible; for example, playing in either of the corners on Fig. 1 will score two wins at once. Making either a tally or a bust will remove the participating cards from the game, freeing those spaces to be used again for future busts or tallies. During the game, the software collects all human-computer interaction, including mouse movements, keyboard, and mouse clicks.

C. Computational Models and Data Analysis

This game is suitable for assessing divided attention because it requires that the player focus on both rows and columns at the same time in order to perform well. Each move is similar and can be treated as a trial in more traditional cognitive experiments, e.g., see Dosher, Sperling, and Wurst [7]. The underlying model of attention allocation is analogous to the resource allocation model [8]. In particular, the total amount of attention, a, allocated on a particular trial i, is the sum of the resources allocated to the rows and the columns:

$$a(t) = a_R(t) + a_C(t) \qquad (1)$$

The goal of the analysis and modeling is to estimate the ability of a participant to allocate attention to both rows and columns at the same time. This requires identification of the subset of moves that can be classified with respect to attention allocation.

TABLE I
ATTENTION ROW/COLUMN CONTINGENCY TABLE

	Column High	**Column low**
Row high	Good Row and Column play	Good Row play Poor Col play
Row low	Good Col play Poor Row play	Less-than-ideal Row and Col play

The placement of a given move result into one of the four categories is based upon relative performance given the board at the time the move was made, rather than actual game performance.

There are only a limited number of moves during a game of 21 Tally that are relevant to the measurement of divided attention. Moves in which players had at least one opportunity to win or bust on both a column and row at the same time were deemed to be relevant to the divided attention model, because they make an immediate distinction between the value of playing a card based on row information versus based on information from columns. For example, the board shown in Fig. 1 would be acceptable according to these criteria because a player *could* win on columns and rows at the same time (by playing on the corners), even though the player need not necessarily do so.

On those moves that can be used to assess divided attention, open spaces can be ranked relative to the ideal play (in other words, ranked by quality) in both rows and columns in order to place a given move onto the contingency table (see Fig. 1). The quality of the different moves can be arranged in the cells of a contingency table, such as Table I.

Fig. 2. A more complex board showing several different move possibilities (shapes) and how they would be placed into the contingency table (numbers). The numbers correspond to the contingency table as in Fig 1. For moves with identical numbers, move quality in absolute game terms is distinguished by shape; the best moves are marked with circles in the upper left corner, squares indicate moderate moves, and the diamond is worst of all. However, this paper deals purely with performance relative to the ideal for rows and columns (shown by the number).

By classifying each eligible move in terms of the four categories in Table I it should be possible to estimate each player's attention allocation on each trial. Note that the key distinction to be made between moves (and between players) with respect to attention allocation exists on the diagonals of this table; moves consistent with divided attention will fall in the upper left quadrant, while those who are merely switching back and forth between attention paid to rows and columns in an undivided way will fall in the lower-left to upper-right diagonal.

TABLE II
SELECTED USERS' PERFORMANCE PERCENTAGES

User#	CandR	CnoR	RnoC	Neither	Moves
1021	0.81	0.09	0.09	0	8272
2020	0.81	0.11	0.08	0.01	18558
1033	0.77	0.1	0.12	0.01	568
1030	0.56	0.22	0.16	0.06	61
2024	0.5	0.16	0.27	0.07	873
1506	0.5	0.28	0.19	0.03	51

"CandR" represents the ideal move for both column and row, "CnoR" represents ideal column but not row, and so forth. "Moves" is the total number of moves the player made that were relevant to divided attention (see "Data Analysis," above).

It is important to note, however, that in this early phase of analysis all potential moves are divided into these four categories by comparing them to the ideal move for either row or column, *not by considering the value of the actual move*. For example, in Fig. 2, several different "flavors" of move can be seen for both type 2 (ideal column but not ideal row) and type 4 (neither ideal column nor ideal row). Worse moves are marked by squares and diamonds; the 2 with a square is a bust on the row and a win on the column, as opposed to merely a win on the column 2 with a circle. Since it is possible to win on both rows and columns on this board (marked by the 1), however, both of these moves would be considered a sub-ideal play in the row direction. Likewise, the different shapes with number 4 show different amounts of busts and non-wins; since they are all sub-ideal on both rows and columns, however, they all belong in the lower-right-hand cell of the contingency table.

III. Results

In order to assess attention allocation during each move, it is important to evaluate the probability that that particular move was made by chance. It is intuitively clear that making a move on a board with fewer chances to make an ideal play will result in fewer ideal plays, even if divided attention score remains constant. For example, a player placing a card randomly on the board would have two chances out of 14 to make an ideal play (marked with "1") in the board in Fig. 1, but only one move out of eight to do so in the board in Fig. 2. Thus, the performance of a player must be adjusted for chance behavior. The adjustment for chance placement is based on the assumption that each of the open squares is equally likely. Table II contains a sample of these chance-adjusted contingency scores.

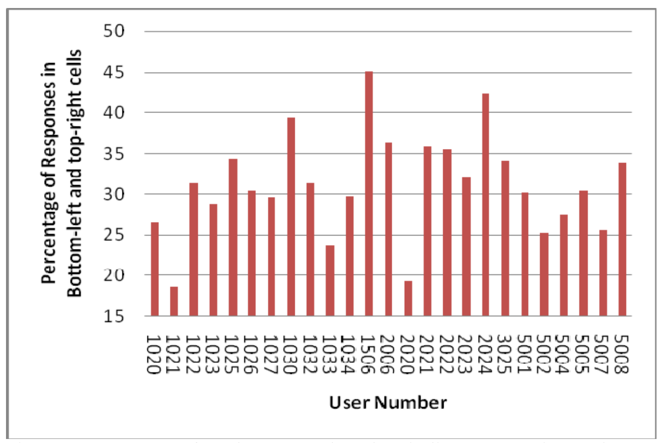

Fig. 3. Percentage of each user's play that indicates attention only one direction at a time (ideal quadrant minus the sum of the minor diagonals).

All players scored at or above 50% in the top-left quadrant of the contingency table. This is to be expected, as the game does reward ideal performance (if it did not, there would be no motivation for the player to divide his attention). The proportion of trials that are consistent with switching rather than dividing attention is represented by the percentage of moves in the bottom-left and upper-right quadrants. These values indicate the percentage of relevant moves that the player spent likely paying attention to only one of the two directions. Regardless of which direction it was (and a given player will often switch several times over the course of a game), the executed moves suggest that the player was not paying attention to both at once. In other words, the player probably was not utilizing divided attention.

By observing the differences between players as regards to single-direction focused attention (see Fig. 3), we can infer differences in divided attention. A description of the detailed analysis of the contingency tables is beyond the scope of this paper; for the purpose of illustration we summarized each player's behavior in terms of the difference between the ideal quadrant and the sum of the minor diagonals. These differences are shown in Fig. 4. Note the large differences, for instance, between player 2 and player 12 (Tables III and IV, Fig. 3).

TABLE III
EXAMPLE CONTINGENCY TABLE FOR USER 1021

User 1021	Column High	Column low
Row high	81%	9%
Row low	9%	1%

The large proportion of moves in the Column high / Row high quadrant, relative to those on the lower-left to upper-right diagonal, suggests a high divided attention score.

TABLE IV
EXAMPLE CONTINGENCY TABLE FOR USER 2024

User 1021	Column High	Column low
Row high	50%	16%
Row low	27%	7%

Note the smaller proportion of moves in the Column high / Row high quadrant, relative to those on the lower-left to upper-right diagonal. This, combined with the difference between the Row low / Column high and the Column low / Row high quadrants indicates that this player focused more on rows than on columns, suggesting a lower divided attention score.

IV. DISCUSSION

A. Practical Value

The ability to monitor and analyze game performance measures which are logically related to divided attention is a far cry from being able to test for and measure divided attention. Nevertheless, we have demonstrated a relatively easy method for calculating a measure of how often a given player plays based on attention paid to a single dimension in a two-dimensional game. It is clear that people differ substantially on the noted measures, as elders are known to have high variability in their divided attention skills. Additionally, this measure is relatively game-skill independent; good or bad game performance can be taken as a measure of divided attention or lack thereof, depending on whether the good or bad play was enacted with regards to both directions simultaneously or not. Skill independence is unusual for game-based performance metrics, and is vital for long-term unobtrusive evaluations, because otherwise the game itself would be influencing the measure over time (i.e., allowing players to "practice").

It is extremely likely that these data contain a great deal of noise and variability which will negatively impact correlation with a standard divided attention test. However, ranking two cognitively healthy people in terms of their relative divided attention is extremely difficult, and scores are highly variable even on the "gold standard" tests [9], [5]. The primary difference between the model presented herein and the standard tests is that the model is based upon a fun (self-motivating), unobtrusive activity that is used multiple times per day. If the values found by the model are consistently lower than the baseline for a given player, or if those values begin to show a trend toward increasing variability, the player can be alerted that they may have a problem with decreased divided attention, and at that point they can seek a neurologist and one of the gold standard tests.

B. Future Work

Several different neurological tests, such as tests of memory, planning, and executive function, have already been administered to the group who produced the data used herein [6]. It is reasonable to think that performance on this game might also correlate to several of these measures. For example, the connection between paying attention to the rows and columns on 21 Tally and the letters and numbers on the Trail-Making Test B (a test of visual, motor, and cognitive ability) is not difficult to imagine, and if true would provide another useful unobtrusive measure of cognitive health. We intend to explore these potential connections between game performance and cognition in the near future.

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REFERENCES

[1] Callahan C, Hendrie H, Tierney W. Documentation and evaluation of cognitive impairment in elderly primary care patients. American College of Physicians. 1995;122:422-429.

[2] Chen P, Ratcliffe G, Phil D, Belle S, Cauley J, et al. Cognitive tests that best discriminate between presymptomatic AD and those who remain nondemented. Neurology. 2000;55:1847-1853.

[3] Jimison H, Pavel M, Wild K, et al. Embedded assessment of cognitive performance with elders' use of computer games in a residential environment. Proceedings of the Workshop on the Cognitive Science of Games and Gaming. 2006.

[4] Jimison HB, Pavel M, Bissell P, McKanna J. A framework for cognitive monitoring using computer game interactions. Studies in Health Technology and Informatics. 2007;129(2):1073-1077.

[5] Scalf PE, Colcombe SJ, McCarley JS, et al. The neural correlates of an expanded functional field of view. The Journals of Gerontology, Series B, Psychological Sciences and Social Sciences. 2007;62(1):32-44.

[6] Jimison H, Jessey N, McKanna J, Zitzelberger T, Kaye J. Monitoring computer interactions to detect early cognitive impairment in elders. Proceedings of the First Distributed Diagnosis and Home Healthcare Conference. 2006; 75-78.

[7] Dosher BA, Sperling G, Wurst SA. Tradeoffs between stereopsis and proximity luminance covariance as determinants of perceived 3D structure. Vision Research. 1986;26(6):973-90.

[8] Kramer AF, Wickens CD, Donchin E. Processing of stimulus properties: evidence for dual-task integrality. J Exp Psychol Hum Percept Perform. 1985 Aug;11(4):393-408.

[9] Edwards JD, Ross LA, Wadley VG, Clay OJ, Crowe M, et al. The useful field of view test: normative data for older adults. Arch Clin Neuropsychol. 2006 May;21(4):275-86.