DTU Library

Body and Brain Training with Big Data and AI

Lund, Henrik Hautop ; Liu, Yan-Xin; Leggieri, Massimiliano

Published in:
Proceedings of the 2020 International Conference on Artificial Life and Robotics

Link to article, DOI:
10.5954/ICAROB.2020.IS2-1

Publication date:
2020

Document Version
Publisher's PDF, also known as Version of record

Body and Brain Training with Big Data and AI

Henrik Hautop Lund, Yan-Xin Liu, Massimiliano Leggieri
Center for Playware, Technical University of Denmark, Building 326,
2800 Kgs. Lyngby, Denmark
E-mail: hhl@playware.dtu.dk, maxleggieri@gmail.com
www.dtu.dk

Abstract

Utilizing a Big Data and AI approach, we developed a novel playful method for screening people for potential physical and cognitive shortages. The method creates a body and brain performance map for each individual, and the Big Data analysis provides a basis for automatically identifying the particular abilities, which may be underperforming in an individual. Further, several studies including randomized controlled trials with the Moto Tiles system have shown that particular Moto Tiles game play will increase performance of particular abilities, even after short-term play. Thereby, the proposed system can automatically generate personalized training protocols for the individual by selecting and providing the right Moto Tiles games for the individual to play to improve the underperforming abilities. The suitability of the method was tested in a small effect test with seniors with mild dementia at a care institution in Denmark. The results show that the seniors with dementia who were screened to be at high risk of falling, within the short period of training with the automatically generated personalized protocol increased their skills to no longer be at risk of falling.

Keywords: Playware, cognition, aging, game.

1. Introduction

With the demographic development, the population worldwide is changing towards having a composition of more senior citizens. In Japan in 2016, 27.3% of the population was aged over 65 years old [1], and many countries are moving towards a similar demography with many seniors [2].

As the percentage of seniors is rising, the absolute number of age-related health issues in the population will also rise. This is a challenge both for the individual well-being, and for the society economics. The increased public expenditure to age-related health issues may become a major expenditure for the society, unless some solutions are found to reduce these age-related health issues or to reduce the costs related to these issues. Some of the most common health issues, which will increase with the increased number of seniors include hypertension, coronary heart disease, type 2 diabetes, osteoarthritis, falls-related injuries, stroke, and dementia.

Technological development may help confronting this challenge. This can be achieved by combining a number of recent advances. On one side, playware development provide the possibility to create intelligent hardware and software that mediates playful actions among users of all ages [3-4]. The advantage of providing such playware within health may be that users will be intrinsically motivated to perform actions with the playware, and these intrinsically motivated actions may be of value to their health. Secondly, as a playware health technology, the Moto Tiles [5] were developed and proved to significantly improve the balance of older adults with less training period than ordinary training [6-8]. Also, Liu et al. [9] presented a Moto Tiles training regime, which could enhance cognitive abilities such as the reaction speed of the seniors. Thirdly, the development of the field of Big Data may allow the development of an AI expert system, which can potentially recognize health patterns of the population and the individual. In this work, we will combine the playware technology, health technology, Big Data and AI to provide a system, which can screen for specific health related challenges for the individual senior, and at the same time automatically generate a personalized playful training for the individual to improve on those identified challenges.

2. Big Data approach for Body & Brain Age Test

As described in Liu et al. [10], we developed a Moto Tiles Body & Brain Age Test based on four Moto Tiles games, each evaluating some body or brain abilities. Each of these games called Color Race, Special One, Final Countdown, and Remember (Simon Says in a newer version) lasts for 30 seconds making the test last for just 2 minutes in total. The physical layout of the Moto Tiles is 6 tiles in a horseshoe shape as shown in Fig. 1.

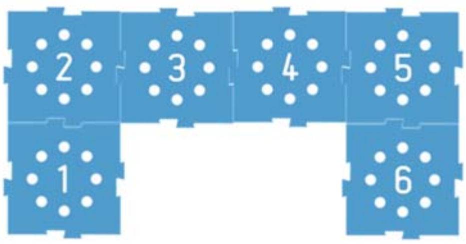

Fig. 1. The Moto Tiles layout for the Body & Brain Age Test.

Expanding on the approach from Liu et al. [10], using a Big Data approach, we collected data from 379 individuals aged 4-97 and analyzed the data. As an example, the collected data from the Moto Tiles Body & Brain Test can be visualized as in Figure 2 for the four test games.

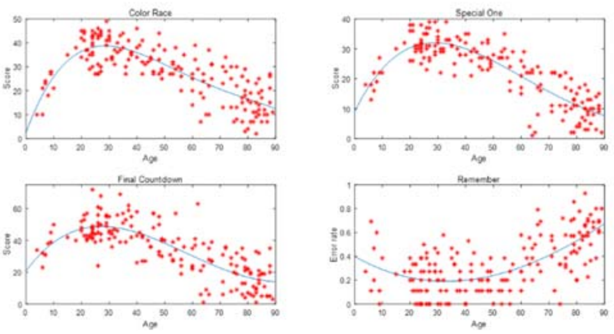

Fig. 2. The age-score model.

Analyzing the data, we can obtain the normative scores of different ages, e.g. as the average score in a game for each particular age, or by polynomial fitting using the procedure described in Liu et al. [10]. The line in Fig. 2 shows the polynomial fitting for each of the four games in the Moto Tiles Body & Brain Test.

3. Falls Risk Screening

Previous work (Liu et al. [11]) has shown that there is a strong correlation between Moto Tiles game tests and standard health tests such as Timed Up & Go (TUG) [12], Chair Stand (CS) [13], and Four Square Step Test (FSST) [14]. The TUG test measures the time that a subject takes to rise from a chair, walk three meters, turn around, walk back to the chair, and sit down. Typical cut point of the TUG test is 14 seconds [12]. The CS test measures the time that a subject takes to stand up from a chair and sit down five times. The cut point of the CS test for fall risk is 15 seconds [15]. In the FSST test, subjects are required to step as fast as possible into each square with both feet in a sequence clockwise and counterclockwise. The cut point of the FSST test for fall risk is 15 seconds [14].

Based on the data of the 51 participants (avg. 80.1 years old) who took both the Moto Tiles physical tests and Body & Brain Age Tests in Liu et al [10-11] tests, we analyzed the correlation between their performances of the two tests, which is shown in Table 1. It can be seen that the Color Race game had strong correlations with the TUG and FSST test ($|r_s| > 0.7$), and the Special One game also had a strong correlation with the FSST test. All the rest cases were moderate correlation.

Table 1. Spearman's coefficients between the physical tests and the Moto Tile games.

Correlation	Color Race	Special One	Final Countdown
TUG	-0.70611	-0.60695	-0.61745
CS	-0.51659	-0.42619	-0.45566
FSST	-0.80849	-0.70577	-0.65266

The cut points of the TUG, CS, and FSST tests for fall risk assessment are 14s, 15s, and 15s respectively. Linear regression models of the games and tests were built in order to transfer the standardized cut points to the games. Table 2 shows the cut points of the three games calculated from the three tests. The results calculated from different physical tests are consistent with each other, which indicates a high reliability of the games. By taking the average of the results, we could recommend the following Moto Tiles game cut points: Color Race = 19; Special One = 13; Final Countdown = 20.

Table 2. The cut points of the Moto Tile games

Cut point	Color Race	Special One	Final Countdown
TUG	19 (18.56)	13 (12.58)	20 (19.75)
CS	19 (19.26)	13 (12.92)	20 (20.32)
FSST	19 (18.69)	13 (12.66)	20 (19.81)

With these correlations verified, the perspective of the Moto Tiles Body & Brain Age Test is that this test can be used as a screening of the population. In this case, with the correlation with the well-established cut-points for falls risk, the Moto Tiles Body & Brain Test is a valid detector of fall risks. In this case, the scoring in the Moto Tiles games Color Race < 19 points, or Special One < 13 points, or Final Countdown <20 points indicates a high risk of multiple falls.

4. Physical and Cognitive Abilities

After being able to perform test and risk analysis with the Moto Tiles Body & Brain Age Test, it is possible to develop a system, which automatically recommend and generates personalized training protocols.

Firstly, the age-score model is integrated into the Moto Tiles Body & Brain Age Test app, which allows users to compare their scores with the normative score at their age. The comparison result is presented as a percentage difference as follows:

$$PD = (score - nv)/nv * 100\%$$

Where PD is the percentage difference and nv is the normative value.

In the Moto Tiles Body & Brain Age Test, four games are employed and the test results are presented as a spider web with 7 abilities (physical and cognitive abilities). Based on the relation between the abilities and the games, the ability scores (0-100) are calculated as follows:

$$Speed = PD_{FC} + 80$$
$$Agility = PD_{CR} + 80$$
$$Endurance = 100 - 10 * (FCscore_{2-9} - FCscore_{23-30})$$
$$Balance = (PD_{CR} + PD_{SO} + PD_{FC}) / 3 + 80$$
$$Memory = PD_{Remember} + 80$$
$$Concentration = PD_{SO} + 80$$
$$Orientation = PD_{CR} + PD_{SO} + 80$$

The algorithm maps the normative values to 80 points. Note that the endurance score is not calculated from the age-score model. Instead it measures if a player performs worse at the end of the game (23-30 seconds) than at the beginning (2-9 seconds) of the game.

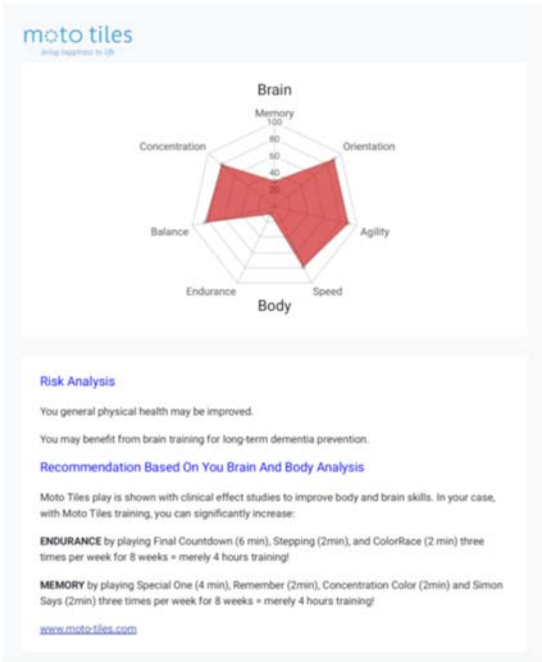

Fig. 3. Screen-shot of the spider web showing the user's score on the seven physical and cognitive abilities.

5. Automatically generated personalized protocol

The personalized training protocol is generated based on the spider web. Seven games are chosen for the protocol: Color Race, Special One, Final Countdown, Reach, Hit the Target, Simon Says, and Concentration. In order to choose appropriate games for the training protocol, each game is firstly assigned with a weight according to the spider web:

$$w_{cr} = 400 - (speed + agility + balance + orientation)$$
$$w_{fc} = 200 - (speed + endurance)$$
$$w_{htt} = 200 - (speed + agility)$$
$$w_{reach} = 200 - (agility + balance)$$

$$w_{so} = 300 - (orientation + concentration + balance)$$
$$w_{ss} = 200 - (memory * 2)$$
$$w_{conc} = 200 - (memory + concentration)$$

The weights of most games are associated with the sum of two abilities or a double of one ability, except for Color Race with four and Special One with three. This is because Color Race and Special One are two fundamental games which are relatively easy to be understood, and they therefore have more chance to appear in the training protocol.

Then the number of games *N* and total training time *T* are defined. In the first trial, $N = 2$ and $T = 7$ minutes. In later weeks of the training, N is raised to 3. The first N games with greatest weights are selected. The training lengths of the selected games are calculated as below:

$$T_i = \frac{w_i}{\sum_{j=1}^{N} w_j} * T$$

6. Discussion

The Moto Tiles games can be used as health tests for the seniors, and that scoring Color Race < 19 points, or Special One < 13 points, or Final Countdown <20 points indicates a high risk of multiple falls. Further, it shows that the Moto Tiles game is a very consistent and robust test.

This means that just by seniors playing and having fun on the Moto Tiles, it is possible to automatically at the same time obtain an indication of their health status and their risk of falls. Further, other scientific effect studies show how balancing skills are improved dramatically while playing on the Moto Tiles, so the Moto Tiles system also presents a tool to lower such risk of falls by playing certain games on the Moto Tiles.

Additionally, the health tests may show other indications. For instance, FSST times of 11 seconds are able to differentiate between persons with chronic stroke and healthy adults older than 50 years, so this can also be recognized simply by playing on the Moto Tiles. Similarly, for CS a score >13.6 seconds is associated with increased disability and morbidity (Guralnik et al, 2000), and metaanalysis results “demonstrated that individuals with times for 5 repetitions of this test exceeding the following can be considered to have worse than average performance” (Bohannon, 2006):

60 - 69 y/o 11.4 s; 70 - 79 y/o 12.6 s; 80 - 89 y/o 14.8 s

Also, TUG is a predictor for global mortality (also after presence of cardiovascular disease was taken into account). Hence, different cut-off points in the Moto Tiles games can be used to show various health related issues (diagnoses) when people are simply playing the games and are having fun.

References

1. *Japan Statistical Yearbook 2018*, Statistics Bureau, Ministry of Internal Affairs and Communications, 2018.
2. D.E. Bloom, A. Boersch-Supan, P. McGee, A. Seike, Population aging: facts, challenges, and responses, *Benefits and compensation International*, 41 (2011) 22.
3. H. H. Lund, and C. Jessen, “Playware - Intelligent technology for children’s play,” Technical Report TR-2005-1, June, Maersk Institute, University of Southern Denmark, 2005.
4. H.H. Lund, T. Klitbo, and C. Jessen, “Playware Technology for Physically Activating Play”, Artificial Life and Robotics Journal, 9:4, 165-174, 2005
5. http://www.moto-tiles.com/
6. H.H. Lund, Play for the elderly-effect studies of playful technology, in *International Conference on Human Aspects of IT for the Aged Population* (2015), pp. 500-511.
7. H.H. Lund, J.D. Jessen, Effects of short-term training of community-dwelling elderly with modular interactive tiles, *GAMES FOR HEALTH: Research, Development, and Clinical Applications*, 3 (2014) 277-283.
8. H.H. Lund, J.D. Jessen, Effect of playful balancing training-a pilot randomized controlled trial, *2013 ISAROB*, (2013).
9. Y. Liu, H.H. Lund, L. Wu, Playful Cognitive Training with Physical Interactive Tiles for Elderly, in *2018 International Conference on Information and Communication Technology Robotics (ICT-ROBOT)* (2018), pp. 1-4.
10. Y. Liu, M. Leggieri, H. H. Lund, Playful Body and Brain Test with the Moto Tiles, in Proceedings of ICAROB 2019, Beppu, Oita, Japan, 2019
11. Y. Liu, M. Leggieri, H. H. Lund, Electronic Measurement and Gamification of Balance Tests, in Proceedings of ICAROB 2019, Beppu, Oita, Japan, 2019
12. A. Shumway-Cook, S. Brauer, and M. Woollacott, "Predicting the probability for falls in community-dwelling older adults using the Timed Up & Go Test," *Physical therapy,* vol. 80, pp. 896-903, 2000.
13. .J. M. Guralnik, E. M. Simonsick, L. Ferrucci, R. J. Glynn, L. F. Berkman, D. G. Blazer*, et al.*, "A short physical performance battery assessing lower extremity function: association with self-reported disability and prediction of mortality and nursing home admission," *Journal of gerontology,* vol. 49, pp. M85-M94, 1994.
14. W. Dite and V. A. Temple, "A clinical test of stepping and change of direction to identify multiple falling older adults," *Archives of physical medicine and rehabilitation,* vol. 83, pp. 1566-1571, 2002. 15. S. L. Whitney, D. M. Wrisley, G. F. Marchetti, M. A. Gee, M. S. Redfern, and J. M. Furman, "Clinical measurement of sit-to-stand performance in people with balance disorders: validity of data for the Five-Times-Sit-to-Stand Test," *Physical therapy,* vol. 85, pp. 1034-1045, 2005.