Modelling the Training Process

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Abstract

In this paper we propose a parametric model of the training process which includes the skill increase and retention during training. The model is verified with the data from 22 subjects performing tasks in a flight simulator. The resulting computational model estimates the behavioral score.

I. Introduction

Adaptive training has been defined as, "training in which the problem, the stimulus, or task is varied as a function of how well the trainee performs" [1]. Across a range of populations and learning contexts, this type of training has been shown to outperform comparative training that is non-adaptive, or fixed [2]. Virtual-Reality offers new opportunities for applying this type of training [3] and has already demonstrated its effectiveness across a variety of simulated tasks [4]. By creating a computational model of the training process, we can automatically select new training scenarios that optimize the learning path, resulting in faster and better training.

II. Modeling

We assume that the training process consists of performing activities in indivisible sessions with small duration. By repeating these sessions multiple times, the trainee builds the desired skill. The performance of the trainee in each session can be evaluated and scored with a positive real number between 0 and 1. We further use a set of L training scenarios ordered by increasing difficulty d_l.

At every given moment n the performance score $Q_k^{(n)}(d_l)$ of the trainee k will depend on the difficulty level of the scenario d_i, a dimensionless positive number. The absolute skill level $S_k^{(n)}$, a dimensionless positive number, of the trainee k at given moment n does not depend on the difficulty of the scenario. We can model the performance score of trainee k at moment n for scenario with difficulty d_i and absolute skill level $S_k^{(n)}$ as:

$$Q_k^{(n)}\left(S_k^{(n)}, d_l^{(n)}\right) = M_l\left(1 - \exp\left(-\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2}\right)\right) + \mathrm{N}\left(0, q^2\right) \qquad (1)$$

Here $\mathrm{N}\left(0, q^2\right)$ is a Gaussian random variable with variance q^2 to model the variation in the subject's performance. The first component M_i is a scenario-dependent maximum achievable score.

Given time without training and refreshing skills, the absolute skill decreases. At the n-th trial we model the forgetting factor as decrease of the absolute skill:

$$S_k^{(n)} = \exp\left(-\frac{\left(t_k^{(n)} - t_k^{(n-1)}\right)}{\tau}\right) S_k^{(n-1)} \qquad (2)$$

where $t_k^{(n)}$ is the time when subject k toke the training session n, and τ is the forgetting time constant assumed constant and independent of subjects and scenarios.

After completing each session, the absolute skill level increases to reflect the learning progress during the session. This increase depends on the difficulty of the scenario according to the Yerkes-Dodson Law [5]: A scenario that is too easy or too hard will result in a non-optimal state of arousal, and a slower learning speed. With optimal difficulty that corresponds to the trainee's absolute skill level the subject increases the absolute skill level fastest. We model this process of increasing the trainee's absolute skill level as follows:

$$S_k^{(n+1)} = S_k^{(n)} + \mu_k \frac{S_k^{(n)}}{d_l^{(n)}} \exp\left(-\frac{\left(S_k^{(n)}\right)^2}{2\left(d_l^{(n)}\right)^2} \right) \tag{3}$$

Here trainee k with absolute skill level $S_k^{(n)}$ at moment n completes a scenario with difficulty d_l and increases the absolute skill level to $S_k^{(n+1)}$ after that. Note that μ_k is the personal learning rate of this individual.

Let assume that we have a set of L scenarios with unknown and different difficulties $\mathbf{D} = \left[d_0, d_{1,}, \ldots, d_L\right]$ with unknown score limitations $\mathbf{M} = \left[M_0, M_{1,}, \ldots, M_L\right]$. A group of K trainees goes through a sequence of N of these scenarios and receives the corresponding performance scores. The training scenarios can happen in one or more days, with or without breaks. This is reflected in the sequence $\mathbf{T}_k = \left[t^{(0)}, t^{(1)}, \ldots, t^{(N-1)}\right]$. Each trainee is characterized by two unknown numbers: the initial absolute skill level $S_k^{(0)}$, and the learning speed μ_k, assumed constant during the training process. As input data we have K sequences of N triplets $\left[d_l^{(n)}, Q_k^{(n)}, t_k^{(n)}\right]$. The total number of data points is $K*N$. Unknowns are L difficulties of the scenarios, L score limitations, the forgetting factor τ, and $2K$ parameters of the trainees, with total number of unknowns $2L+2K+1$. In most of the cases $2L+2K+1 < K*N$ and this highly nonlinear system of equations is solvable.

III. Dataset

We have a dataset with scores $Q_k^{(n)}$ from $K = 22$ subjects performing scenarios with $L = 2$ levels of difficulties for 20 iterations in five consecutive days. For some of the subjects we have skills retention checks at 60th and 90th days with 20 more scenarios for each day. In this data collection, the scenarios of two levels of difficulty are performed alternatively by the trainees.

IV. Results

After solving the system of equations via mathematical optimization, the performance scores are predicted by the model with deviation of 6.34 points, the forgetting time constant is 800.06 days.

V. Conclusion and Discussion

An accurate computational model with the mean and the variation of the average initial skill level and learning rate can generalize the behavioral score in normal population and therefore save the real-world training time and cost. Future work includes exploring various training strategies and deriving the optimal approach for training.

References

[1] M. Zahabi, AM Abudl Razak, "Adaptive virtual reality-based training: a systematic literature review and framework." *Virtual Reality*, 2020/24 (4), 725–752.

[2] CR Kelly, "What is adaptive training." *Human Factors, 1969/11 (6):547-556*

[3] D. Rodenburg, P. Hungler, S.A. Etemad, D. Howes, A. Szulewski & J Mclellan, "Dynamically adaptive simulation based on expertise and cognitive load." Proc. 2018 IEEE Games, Entertainment and Media Conference 2018:1-6

[4] K. Ahir, K. Govani, R. Gajera, M. Shah, "Application on Virtual Reality for Enhanced Education Learning, Military Training and Sports". *Augmented Human Research* 2019/5(1), 1–9.

[5] RM Yerkes, JD Dodson, "The relation of strength of stimulus to rapidity of habit-formation". Journal of Comparative Neurology and Psychology, 1908/18 (5): 459–482.