Adaptive Training System

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***Abstract*—In this paper, we propose an adaptive training algorithm that accelerates the training process based on a parametric model of trainees and training scenarios. The proposed approach makes trial-by-trial recommendations on optimal scenario difficulty selections to maximize improvements in the trainee's absolute skill level.**

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]. Researchers have shown that this type of training outperforms comparative training that is non-adaptive or fixed across a range of populations and learning contexts [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 using a computational model of the training process, we can derive recommendations for optimal scenario difficulty, resulting in faster and enhanced training.

II. Optimal Scenario Difficulty

We assume that the training process consists of performing activities in indivisible sessions with short duration. By repeating these sessions multiple times, the trainee builds the desired skill level. The performance of trainees in each session can be evaluated and scored with a positive real number between 0 and 100. We further use a set of L training scenarios ordered by known difficulty d_l and known maximum achievable score M_l.

Inspired by the Yerkes-Dodson Law [5] as described in [6], a parametric model of the training process is created. In this model each trainee k at session n is characterized by their absolute skill level $S_k^{(n)}$, their learning speed μ_k, and forgetting factor τ_k. The training step n, with scenario difficulty d_l, the trainee k is modelled as:

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

$$\hat{Q}_k^{(n)} = M_l \left(1 - \exp\left(-\frac{(S_k^{(n-1)})^2}{2(d_l^{(n)})^2}\right)\right) + N(0, \sigma_l^2) \tag{2}$$

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

Equation (1) accounts for absolute skill deterioration with time, Equation (2) estimates the score accounting for the random component of human performance, and Equation (3) computes the increase of the absolute skill of the trainee.

TABLE I
Distribution of the trainees characteristics.

Parameter	Average	Deviation
Initial skill	1.7031	0.5397
Learning coefficient	0.2190	0.4020
Forgetting factor, days	800.06	0.0000

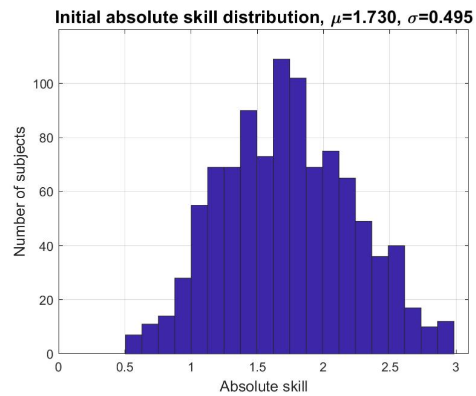

Fig. 1. Initial absolute skill distribution.

The increase of absolute skill depends on the factor after the learning speed μ_k in the third equation. After taking its first derivative, assigning it to zero and solving for d_l, the fastest increase of the absolute skill happens at $d_l^{(n)} = S_k^{(n)}$.

Given the training history (previous scores on scenarios with known difficulties), we can estimate the trainee's initial absolute skill and learning rate, then model the training process and estimate the current absolute skill, leading to the recommended difficulty for the next training scenario.

III. Dataset

To evaluate the proposed approach, we created a synthetic dataset of 1,000 trainees with random initial skills and learning speeds that meet the statistical distribution of these parameters from a group of 22 trainees from previous data collection. The distribution of the parameters is modeled as Gaussian, characterized by mean and variance. The specific numbers are shown in Table I. The absolute skill distribution is pruned to $[0.5, 3.0]$, as shown in Fig. 1. Similarly, the learning rate is pruned to $[0.05, 1.0]$. These trainee parameters are assumed to be $unknown$ during the adaptive training process.

TABLE II
RESULTS FOR GROUP AND INDIVIDUALIZED TRAINING.

Training strategy	Group training			Individualized training		
	Sessions	Days	Weeks	Sessions	Days	Weeks
Fixed difficulty	346500.0 ± 37447.1	17800.0 ± 1967.8	4000.0 ± 0.0	93266.5 ± 3789.9	6215.4 ± 217.4	1613.7 ± 48.8
Adaptive difficulty	261175.0 ± 28626.4	13533.0 ± 1442.1	3000.0 ± 0.0	68947.7 ± 2989.2	4792.4 ± 191.4	1382.2 ± 40.3
Reduction, %	24.62	23.97	25.00	26.07	22.89	14.35

The training is assumed to contain 20 scenarios with absolute difficulty ranging from 1 to 20 and maximum score ranging from 95 down to 45 points, i.e., each unit of difficulty increase leads to a 2.5-point decrease in the maximum possible score. These parameters are assumed to be $known$ during the adaptive training process.

IV. TRAINING PROCESSES, APPROACHES AND STRATEGIES

We assume that the training goal is for 95% of the trainees to reach 75 points in three consecutive runs on a scenario with difficulty 6. The training process happens in two blocks per day, 10 runs per block. We can execute a *group training* approach, where the training ends when the entire group meets the training goal, or an *individualized training* approach, where each trainee ends the training when they reach the training goal. The training process can happen using two training strategies: *fixed scenario difficulty* (6 in our case, baseline), or *adaptive scenario difficulty* – the subject of this paper. In all cases, the training cost is measured by the total number of training runs, days, or weeks.

V. ALGORITHM

To recommend the optimal difficulty for the next training run, we need to estimate the trainee's initial skill $S_k^{(0)}$ and learning rate μ_k. To do this, we use past scores, scenario difficulties, and training days. At the beginning of the n-th run, we have $n-1$ triplets $[Q_k^{(n-1)}, d_k^{(n-1)}, t_k^{(n-1)}]$. Given an initial arbitrary $S_k^{(0)}$ and μ_k, we can simulate all steps and compute an array of $n-1$ scores $\tilde{Q}_k^{(n)}$. Then, we can find the trainee's initial skill $S_k^{(0)}$ using a constrained optimization method:

$$[S_{k0}, \mu_k] = \arg\min_{S_{k0}, \mu_k} \left(\sqrt{\frac{1}{n-1} \sum_{\nu=1}^{n} \left(Q_k^{(\nu)} - \tilde{Q}_k^{(\nu)} \right)^2} \right) \quad (4)$$

During optimization, we determine the current skill level $S_k^{(n-1)}$, which we use to recommend the scenario difficulty $d_l^{(n)}$ for the next n-th step.

VI. RESULTS

Table II compares the total training time required for the fixed and adaptive difficulty training as measured in sessions, days and weeks, and reports the reduction in training time. As shown in Figure 2, the adaptive training system can shorten the training time $14-26\%$, compared to fixed scenario difficulty for the individualized approach. To provide a statistical range, the process of training was simulated 120 times with ten different randomly generated data sets and 12 times execution of each training set, which also carries a random component - human performance variation.

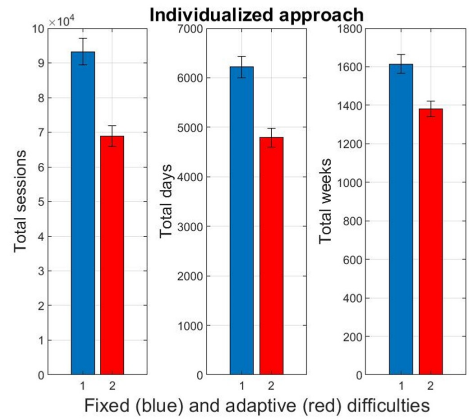

Fig. 2. A figure presenting the required training time for the Fixed Difficulty and Adaptive Difficulty training approaches.

Replacing the group approach with an individualized approach can reduce the training cost by more than half in both fixed and adaptive training approaches. The two approaches combined lead to substantial savings in training costs. If we have a fixed training time (number of runs), then the adaptive training system maximizes the trainee's absolute skill.

The proposed approach is capable of using both behavioral scoring and scoring with physiological data.

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