IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal
SPECIAL SECTION ON SMART HEALTH SENSING AND COMPUTATIONAL INTELLIGENCE: FROM BIG DATA TO BIG IMPACTS

Received March 18, 2019, accepted May 14, 2019, date of publication May 24, 2019, date of current version June 7, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2918846

A Visuo-Haptic Attention Training Game With Dynamic Adjustment of Difficulty

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This work was supported by the National Key Research and Development Program under Grant 2017YFB1002803, and in part by the National Natural Science Foundation of China under Grant 61572055.

ABSTRACT While action video games have been shown effective for training attention, little research has explored how to effectively utilize haptic interaction in these games for attention modulation and training. In this paper, we introduce a visuo-haptic game combining fingertip force control with an immersive visual display. In the proposed stimulus-reaction game, users are required to press a force sensor using either the index or middle finger from both hands. In order to be successful in a trial, users must respond swiftly to the visual cues by producing an accurate fingertip force within an allowable duration of time. The difficulty levels of the task are adjusted dynamically by an adaptive model to achieve a constant success rate. Validation tests on 12 participants confirmed that the proposed model is actually able to maintain an expected success rate of 75% within ± 5% fluctuation. With the proposed game, 12 trainees were subsequently administered pre- and post-tests in the first and last day of a longitudinal experiment to examine efficacy of training on the sustained-attention-to-response task (SART) and the Stroop task. The results from these two typical batteries of attention test show that significant improvements were found after five days of attention training. Overall, these data illustrate the potential of the proposed visuo-haptic game for attention training.

INDEX TERMS Attention training, dynamic adjustment of difficulty, finger force control, success rate, visuo-haptic game.

I. INTRODUCTION

Sustained attention is a key cognitive skill for both clinical and healthy populations. Enhancing sustained attention by training has a potential role in several applications including treatment of cognitive disorders such as attention deficit hyperactivity disorder (ADHD) [1]. Various medications have been developed to help manage hyperactivity and inattention in children [2]. Whereas, the medications failed to produce same results and did not present to have long-term effects. Cognitive behavioral therapy, like cognitive training, has demonstrated favorable long-term effects on everyday functional outcomes in older adults [3]. Moreover, there also is a growing interest in developing methods of attention enhancement for healthy adults, for example, to accelerate learning and skill acquisition in complex tasks that would otherwise take very long to master [4]. Although there are many cognitive training techniques, as discussed in other papers [5], [6], gamification-based attention training is a low-cost, portable method that is particularly well-suited for practical applications and well-tolerated by participants [7].

To date, the majority of studies testing the efficacy of using computer games in attention training have been done with visual and audio modalities, while the potential of the haptic modality has not been effectively exploited in game design. One of our main hypotheses is that an interactive process through haptic-centered multisensory integration would activate attention intensively, and thus foster changes in neuronal activity related to attentional control. This hypothesis is developed from the contextual interference literature that has reliably suggested that both multisensory integration and attentional processes take place and can interact

The associate editor coordinating the review of this manuscript and approving it for publication was Qingxue Zhang.

at multiple stages in the brain [8], [9]. Kampfer *et al.* [10] illustrate how haptic input activates processes that affect human perception of products and ultimately alters behavior and thus substantiates its role in multisensory innovation and product design. This greatly inspires us to confirm this hypothesis with a long-term study divided into two steps: developing and validating a novel attention training game integrating haptic interaction, and then comparing training efficiency with traditional audio-visual games under the same index.

As a first step towards exploring haptics-mediated attention training paradigms, one of our previous studies introduced a gamified visuo-haptic task using finger force control [11]. In the finger force control game, henceforth called ''FF-Dancing'' in this paper, swift force control skill is required for each user to exert an accurate fingertip force within an allowable duration of time in each trial. Even though challenging perceptual tasks require more attention [12], an adaptive strategy is also crucial to matching the difficulty level of game according to user's skill and maintaining a desirable performance for trainees. As a typical index of user performance, the success rate is determined by the user's skills and the task difficulty. Several researchers recommended that a constant success rate of 75% might be optimal to motivate players in attention training games [13], [14]. Therefore, the goal of the adaptive strategy is to dynamically tune the difficulty of the FF-Dancing, making the user's success rate converge quickly and maintaining at about 75%. However, there are two remaining questions in our previous work:

First, what model of dynamic adjustment of difficulty can track the time-varying user's skills, be compatible with individual differences of users, and adapt to random task difficulties?

Second, can the proposed force control game really improve the attentional control skill and can this improvement be generalized into other activities?

In this paper, answers to these two questions are explored after addressing a key technical challenge, which is to formulate dynamic adjustment of difficulty and optimize its parameters in multi-dimensional difficulty space. In the stimulus-reaction task using force control, the success rate of performance depends on three difficulty dimensions: allowable reaction time, target force magnitude, and force tolerance. Fortunately, reaction time is a function of force magnitude and force tolerance based on Fitts' Law in the adopted force control task [15]. Taking advantage of this characteristic, we simplify the three difficulty dimensions into one dimension: the allowable reaction time. Then, we model the dynamic adjustment of difficulty across trials by an iterative formula for adjusting the allowable reaction time. A set of satisfactory model parameters are obtained after repeated adjustments with a large number of pilot experiments. Moreover, a validation test is conducted to confirm the actual performance of the proposed model, and answer the first question mentioned above.

To answer the second question, a longitudinal experiment was subsequently conducted to check the efficacy of the proposed game on attention performance. Recruited trainees are administered pre- and post-tests in the first and last day of a five-day training schedule. The training effect of ''FF-Dancing'' is examined by a test battery consisting of two typical attention tests, a sustained-attention-to-response task (SART) [16] and a revised Stroop task proposed by Moore *et al.* [17]. There are various cognitive test batteries for attention assessment in existing studies [5]. Whereas, to the best of our knowledge, these test batteries have not been coupled with force control task. As a result, after trying one by one from several typical test batteries in pilot experiments, the SART task and the Stroop task are finally selected based on three criteria: test-retest reliability, utility as a repeated measure, and acceptance in attention studies. Compared to participants in a control group without training, the participants in the training group receiving the FF-Dancing training gain significant attention improvement.

The technical contributions of this paper include the following: First, an adaptive model is proposed and experimentally validated for online adjustment of the difficulty level of the force control game to achieve and maintain an expected success rate for users. Second, results of a longitudinal experiment provide an evidence that attention training game involving haptic interaction improves attentional performance.

The remainder of this paper is organized as follows. In Section II, related studies are briefly reviewed. In Section III, we introduce the design rationale and details of the visuo-haptic system. In Section IV, the approach for dynamic difficulty adjustment is detailed to match the skill level of the user. In Section V, an experimental validation is described. In Section VI, a longitudinal experiment of attention training is described. In Section VII, a discussion is presented. Conclusions and future work are provided in the last section.

II. RELATED WORKS

A. COMPUTER GAMES FOR ATTENTION TRAINING

Computer games for attention training have become both a widespread leisure activity and a substantial field of research [18], [19]. Cognitive training games are a kind of customized design games aiming to improve the trainees' cognitive abilities through repeatedly performing cognitive tasks embedded in those games [20]. It is demonstrably feasible to translate traditional evidence-based interventions, such as cognitive behavior therapy, to computer gaming formats [21], [22]. There is evidence to suggest that action games are capable of altering visual attention processing [23]. To exploit the positive benefit of ubiquitous video games, Bavelier *et al.* [24] revealed neural bases of selective attention using two levels of difficulty in action video game players.

How to design a more effective attention training game is still an open topic. The design rational of most attention training games is to attract users' attention by presenting vivid animations, fantastic audio effects and interesting stories [25]. Clemens *et al.* [26] concluded that computer game-like attentional training paradigms, if designed along both clinical as well as theoretical backgrounds, seem to be able to activate the well-known neural correlates of alertness and focused attention. Building on evidence of brain plasticity from rehabilitation science and contemporary developmental neuroscience, cognitive training is premised on the notion that key brain networks implicated in ADHD can be strengthened, and the cognitive processes they subserve can be improved, through controlled exposures to information processing tasks [6], [27]. To provide new engaging rehabilitation tools in particular for boosting attention and well-being, Bavelier and Davidson [28] and other neuroscience scholars advocated the collaboration with game designers to explore effective ways of using interactive technology such as video games. Kiili suggested that the designers of educational multimedia or games consider the utilization of haptic feedback in learning materials to reduce extraneous cognitive load [29].

The effectiveness and potential of incorporating virtual reality (VR) within the treatment of various psychiatric disorders have been summarized in several systematic reviews [30], [31]. When playing video games, players engage in seamless virtual environments with success contingent on the time-pressured deployment. These games recruit flexible allocation of attention as well as precise bimanual motor movements in response to complex visual cues [32]. Rizzo *et al.* [33] developed virtual reality games for the assessment and rehabilitation of ADHD. Their experimental results show that virtual environments delivered via the head mounted display (HMD) are well suitable for attention training as they provide a controlled stimulus environment where cognitive challenges can be presented along with the precise delivery and control of "distracting" auditory and visual stimuli.

Inspired by the studies on the sense of touch from cognitive neuroscience perspective [34], the feasibility of attention training based on haptic interactive game has been a new research interest. Using a PHANToM Premium 3.0 robot, Dvorkin *et al.* [35] designed a "virtually minimal" visuo-haptic training of attention in severe traumatic brain injury. Their experiment confirmed that interactive visuo-haptic environments could be beneficial to attention training for severe TBI patients. However, the lack of progressively increased interactive difficulty levels in their visuo-haptic training led several patients to become bored when they performed the same task in later sessions due to the "ceiling effect" of their performance.

B. METHODS FOR DYNAMIC ADJUSTMENT OF DIFFICULTY

Currently, attention training is typically delivered via computers using adaptive procedures, whereby the difficulty level of training task is automatically increased across sessions to continually challenge a patient at the boundaries of his / her competence [36]. Although sustaining a moderate level of attention is critical in daily life [37], evidence suggests that attention is not deployed consistently, but rather fluctuates from moment to moment between optimal and suboptimal states. Such fluctuations in attention are commonplace, and may even be characteristic of sustained performance [38]. Attention can vary from optimal levels to extremes of either under-engagement (e.g., mindlessly daydreaming while driving) or over-engagement with the task at hand (e.g., overthinking the service in tennis) [39]. To avoid boredom due to the under-engagement (if the game is too easy) or frustration due to the over-engagement (if it is too hard) in the practice session, adaptive control of the difficulty level is a necessary topic in cognitive game design [40], [41].

Dynamic adjustment of difficulty (DAD) is the process of automatically changing parameters, scenarios and behaviors in real time, based on a player's performance. Fluctuations in the player's performance are also commonplace because playing computer games is linked to a range of perceptual, cognitive, behavioral, affective, and motivational impacts and outcomes [42]. An enjoyable game should be able to make players development and master their skills. In order for the player to experience GameFlow, the perceived skills must match the challenge provided by the game, and both challenge and skills must exceed a certain threshold [43]. Consequently, a central challenge for attention training games is to develop an adaptive algorithm that dynamically adjusts the difficulty level to maintain the desired performance of players, thus keeping the user interested from the beginning to the end.

A number of studies in recent years have investigated the DAD mechanism in computer games to automatically tailor gaming experience to an individual player's performance [44]. Silva et al. [45] presented a DAD mechanism for MOBA games. The main idea is to create a computer-controlled opponent that adapts dynamically to the player performance, trying to offer to the player a better game experience. Quantitative and qualitative experiments were performed, and the results showed that the system was capable of adapting dynamically to the opponent's skills. Accordingly, we develop a DAD for force control in our proposed attention training games to maintain the target success rate, as defined by a constant 75% success rate [13], [14]. Briefly, it is promising to design haptics-mediated attention training tasks that could lead to plastic effect of enhancing attention control skill.

III. DESIGN OF THE VISUO-HAPTIC GAME

A. DESIGN RATIONALE FOR ATTENTION TRAINING GAMES

The design rationale of the visuo-haptic game is to tightly integrate the potential of human visual perception and finger force control capability, and thus to produce a high attention workload during the task execution process. The field is in its infancy. Controlled trials are needed to be rigorously designed, adequately powered, and randomized in order to investigate variability of treatment response. Meanwhile, they are also needed to determine mediators and moderators of

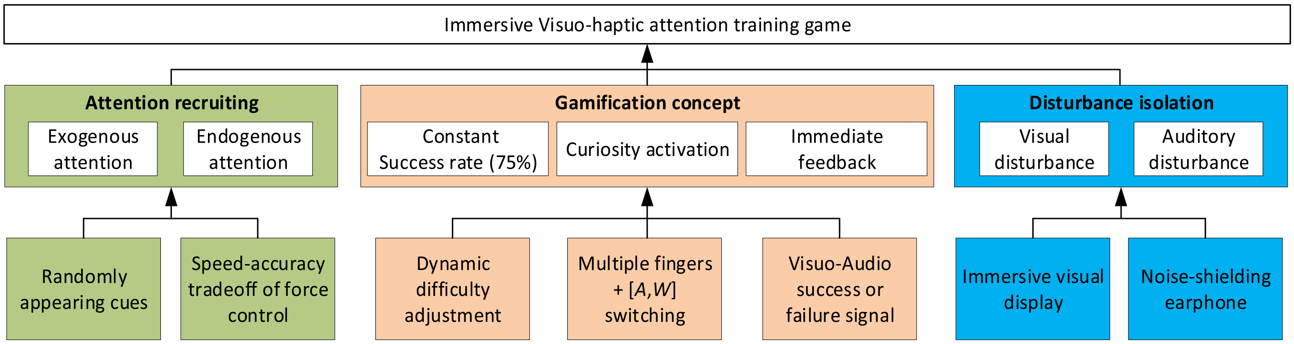

FIGURE 1. Design rational combining three components.

cognitive training effects [6]. All successful video games engender high levels of motivation and arousal and provide immediate informative feedback. They are intrinsically rewarding and utilize difficulty levels that are increased in a manner commensurate with a player's skill. Each of these characteristics is known to foster time-on-task and promote more effective learning [46]. Researchers have attempted to assess potential improvements in sustained attention performance by (1) having participants engage in ''mindful breathing'', (2) inducing a positive rather than a negative mood, (3) providing a self-alertness training strategy, and (4) presenting periodic auditory alerts to bring attention back on task [47]. As shown in Fig. 1, we define three major components in the design rationale of the proposed attention training game: *attention recruiting*, *gamification concept* [40], and *disturbance isolation*.

In the component of *attention recruiting*, the proposed game aims to induce intensive workload on both exogenous and endogenous attention. As Cardoso-Leite *et al.* [48] pointed out, attention can be exogenous or stimulus-driven, automatically capturing resources for the immediate processing of salient or unpredicted stimuli, as when startled by a sudden alarm. Alternatively, attention also can be endogenous or top-down, engaged voluntarily and oriented toward a desired goal as in the case of reading on a crowded bus. Maclean *et al.* [49] found a strong interaction between endogenous and exogenous attention during vigilance performance. Similarly, both endogenous and exogenous attention may be recruited in this stimulus-reaction task, triggering a high-level attention on the users' brain. Specifically, users must perform a quick and accurate force control action within a given time if they want to be successful in reaction to an external cue.

In the component of *gamification concept*, three sub-components are embedded, including constant success rate, continuous vigilance, and immediate feedback. Some sub-components are inspired by the GameFlow model proposed by Sweetser and Wyeth [43]. To ensure the constant success rate 75%, we proposed a dynamic adjustment of difficulty algorithm to match the task difficulty with a player's skill of finger force control. Current hypotheses suggest that critical game characteristics driving 'learning to learn' include variety (of stimuli, actions, inferences, among others) and the need to flexibly utilize attention (either to switch between different characteristics as they become task relevant, or to switch between different states of attention) [46]. Accordingly, randomly appearing visual cues are provided to prompt the player to maintain continuous vigilance. Finally, immediate feedback is necessary to notify the user about his / her performance. There has been converging evidence demonstrating that the focus of attention induced by the instructions or feedback provided to learners can have a significant impact on motor skill learning [50]. As a result, visuo-audio signals of success or failure were used to provide encouraging or punitive feedbacks to the users in time.

In the component of *disturbance isolation*, task-irrelevant distraction from visual and audio channels is shielded to ensure an effective training process. Attention training using virtual reality games is a promising approach since it is capable to shield trainees from the external environment. In a rehabilitation center, for example, an attention training game with HMD allows multiple trainees to play simultaneously in a shared room without being disturbed by each other. Patients report satisfaction with VR-based therapy and feel it is more acceptable than traditional approaches [30]. Moreover, the results from Kober and Neuper [51] validated that increased presence was associated with a strong allocation of attention resources to the virtual reality (VR), which led to a decrease of attention resources available for processing VR-irrelevant stimuli. Under the assumption that haptic feedback would capture, redirect, and help sustain a patient's attention, Dvorkin *et al.* [35] concluded that interactive visuo-haptic environments could be beneficial to attention training of severe TBI patients in the early stages of recovery and warranted further and more prolonged clinical testing.

The experience of haptic interaction is quite distinctive and irreplaceable for users during FF-Dancing gaming, even though multisensory modalities are used with an expectation to obtain better training effect. Firstly, when users wear the HMD to play the FF-Dancing, no visual or auditory modalities can be available except for tactile perception during

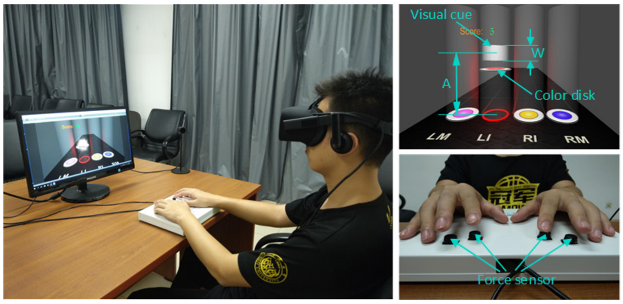

FIGURE 2. **Experimental scenario of the attention training system.**

switching fingers. Wherein, the proprioception is indispensable for user's finger localization and finger praxis which involve movements of the individual fingers [52]. Specifically, only proprioception and touching can be leveraged to correctly choose the executive fingers. Oakley *et al.* [53] defined haptics to be anything relation to the sense of touch and the human haptic system consisting of the entire sensory, motor and cognitive components of the body-brain system. This definition is therefore closest to meaning of the proprioception [53]. Secondly, in other stimulus-reaction tasks responded by keystroke or mouse-click, the up and down of each target require two buttons to be controlled separately. While, the speed and time of the up and down of each target can be deftly controlled by only one force sensor. Hence, users must pay more attention to the speed and accuracy tradeoff in each successful reaction. This was confirmed by participants in one of our pilot experiments in which we used buttons instead of four force sensors. Consequently, the visuo-haptic game may engage more user attention in the reaction using finger force control.

B. THE VISUO-HAPTIC ATTENTION TRAINING GAME

Fig. 2 shows the experimental scenario of the visuo-haptic attention training system. A virtual isolated testing room for the stimulus-reaction task has been developed using Unity 3D (Unity Technologies, UK). All visual information is provided by a HMD (Oculus Rift CV1, Oculus Inc. USA). In the virtual environment, there are four semi-transparent cylinders. At the bottom of each cylinder, there is a color disk that can move on the cylinder. The motion of the disk is controlled by the fingertip force of a user, which is measured by force sensors (FSG15N1A, Honeywell Inc. USA). The proposed game involves the middle and index fingers on both hands, i.e., left middle finger (LM), left index finger (LI), right index finger (RI) and right middle finger (RM). During game playing, a visual cue appears on one of the cylinders, and the user controls the disk to hit the visual cue by pressing the force sensors. It is mandatory that when one finger is pressing, the other fingers must be completely released.

The visual cue is defined by the force parameters. The variables and their definitions involved in this paper are listed in Table 1. As shown in Fig. 2, the height and thickness of the cue indicates the magnitude (A) and the tolerance (W) of

TABLE 1. **Variables and their meanings.**

Category	Variable	Brief Definition
Force control task	F_R	Magnitude of the real finger force (N)
	A	Magnitude of the target force (N)
	W	Tolerance of the target force (N)
	ID	Index of difficulty
	T	Allowable reaction time (ms)
User performance	t	Actual reaction time (ms)
	η_e	Target success rate
	T_D	Dwell time of maintaining force (ms)
	η_k	Real-time success rate of the k^{th} trial
	S_i	Score of the i^{th} trial
Understanding of Fitts' Law	N	Number of trials
	T_p	Basic reaction time to achieve η_e
	T_d	Average margin of reaction time (ms)
	T_{ID}	Reaction time for a given ID (ms)
	ξ	Amplification factor
Coefficient of model	α	Adjustment coefficient for success rate
	β	Adjustment coefficient
	ω	Compensation coefficient
	λ	Compensation coefficient
Iterative computation	T_0	Initial allowable reaction time
	T_k	Allowable reaction time for the k^{th} trial
	t_k	Actual reaction time for the k^{th} trial
	T'_{k+1}	Iterative value of T for the $(k+1)^{th}$ trial
	T_{k+1}	Final value of T for the $(k+1)^{th}$ trial

the target force. The height of a color disk increases along with the magnitude of the real force (F_R). A hit is successful when the real force F_R equals to the target force A within a given tolerance W. Fig. 3 shows the three states of F_R and the corresponding relative positions between the color disk and the visual cue (the grey disk). For example, when F_R is within the tolerance of A, the color disk overlaps with the grey disk.

A fast-paced stimulus-reaction force control task was adopted based on Fitts' Law [11]. To engage the user in the task, we use a randomized algorithm to vary the executive fingertip, force magnitude and tolerance between adjacent trials. We define the actual reaction time (t) is the time consumed from the appearance of a visual cue to the completion of force control in each trial. In order to successfully perform the force control task, the user must quickly move the color disk into the visual cue and keep it inside. The "dwell time" (T_D) of maintaining the color disk in the visual cue should be greater than a predefined threshold 200 ms. The trial is unsuccessful if the user fails to achieve the above force control in the allowable reaction time (T). As shown in Fig. 4-a), a punitive visual and audio feedback is provided to show the failure. If the user successfully completes the force control, the visual cue disappears, and a positive visual feedback is provided as shown in Fig. 4-b). In addition, a melodious piano tone is provided to reward and encourage the player to achieve as

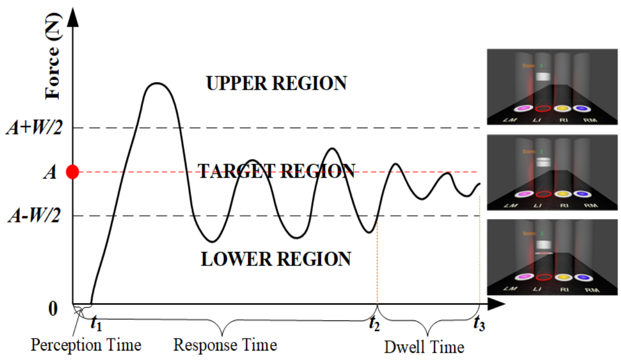

FIGURE 3. Three states of an example profile of the real force.

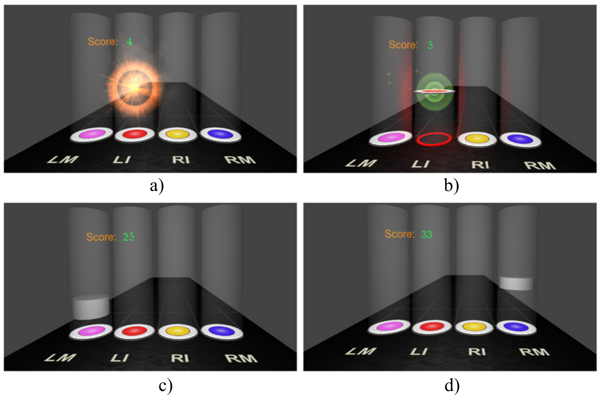

FIGURE 4. Illustration of the visual cue and feedback. a) Feedback of failure. b) Feedback of success. c) LM, [A,W] = [1,0.8]. d) RM, [A,W] = [2,0.5].

many scores as possible. In a word, if t is smaller than T of the current trial, the player will be successful and get a score.

Continuous vigilance is necessary for a user to maintain a state of being very sensitive to incoming cues combined with a readiness to react. As shown in Fig. 4-c) and Fig. 4-d), the visual cue is randomly switched between all pairs of A and W. There are 12 pairs of A and W. A is selected from the set (1, 2, 3 N), while W is selected from the set (0.5, 0.6, 0.7, 0.8 N). The tolerance range is defined symmetrically with respect to the magnitude as: ($A\pm0.25$, $A\pm0.3$, $A\pm0.35$, $A\pm0.4$). To avoid boring and repetitive reaction with a single finger, the executive finger is randomly assigned among the four fingers, and different melodious piano tones are provided for different fingers in the successful trials.

IV. MODELING FOR DYNAMIC ADJUSTMENT OF DIFFICULTY

A. REQUIREMENTS IN DESIGNING THE DAD APPROACH

To adapt dynamic changes of user finger force control performance, we design an online estimator of the allowable reaction time to maintain the target success rate across trials during playing. The success rate in each trial is determined by both the user real-time performance and the task difficulty. Through analyzing the characteristics of the task and the users, we have identified the following three requirements in designing the DAD approach for force control task.

First, a desirable DAD should adapt to uncertain fluctuations in user performance throughout the training process. User's force control performance is always fluctuating under the influence of attention, affective state, and fatigue etc. Consequently, the actual reaction time t in each trial is fluctuating during game playing. Therefore, an adaptive algorithm should be able to consider the fluctuation in order to maintain a constant success rate across trials.

Second, individual difference of force control skill needs to be considered for analyzing human behavior. For a given [A, W], different users definitely produce varied t. Therefore, the DAD approach should be able to identify the user's force control performance in an online strategy and adjust the difficulty level of the task to match with individual capability.

Third, the multi-dimensional behavior of the fingertip force control task must be considered. The difficulty of the task in each trial is determined by three difficulty dimensions: A, W, and T. Simultaneous tuning of these three variables may produce a large solution space, and make it difficult to efficiently find the optimal difficulty level that could match the user's real-time capability. As advocated in a previous study [11], a straightforward strategy for adjusting difficulty level is to use a multiple dimensional optimization approach. The strategy defined the difficulty level of a force control task as a "performance space", which consisted of various combinations of the three dimensions [A, W, T]. However, this approach needs to construct and update a 3D iso-surface, and then requires complex algorithms.

If we can simplify the 3D problem into a 1D problem, it will be available to tune the task difficulty by changing the value of T in each trial, and thus to control the success rate. Attention fluctuations and individual differences can be reflected in the reaction time so that they could be adapted by online adjustment of the allowable reaction time T. Consequently, the first two requirements will be also met by adaptive adjustment of the parameter T.

B. DIMENSION REDUCTION APPROACH

In this section, we propose a dimension reduction approach to simplify the difficulty adjustment in the force control task. Although the logarithmic model proposed by Shannon based on Fitts' law is most frequently used in human computer interaction, the Meyer model is validated to be more suitable for the accurate fingertip force control task, which is defined as [54]. According to the Meyer model, for a given [A, W], the reaction time t can be quantifiable by the model in Eq. (1).

$$\begin{cases} t = a + b \cdot ID \\ ID = \sqrt{A/W} \end{cases} \tag{1}$$

where a and b are regression coefficients, and ID refers to the index of difficulty.

As a result, we can reduce the three-dimensional variables to a one-dimensional variable T in adjusting task difficulty.

Based on the above reasoning, the combination $[A, W]$ is selected as the fixed variables, and the allowable reaction time T is adopted as the difficulty variable, which is modulated dynamically according to the user's force control skill.

Furthermore, to maintain user engagement, random switching between varied combinations $[A, W]$ is introduced for adjacent trials. Whereas, due to the random selection of $[A, W]$ from the 12 combinations in each trial, the difficulty for the next trial should be adjusted according to the performance metrics detected in the previous trials with the same $[A, W]$. Correspondingly, an independent queue is defined for each $[A, W]$ to modulate the allowable reaction time in a parallel style.

As a consequence, independent queues (Q_i, $i = 1, 2, \ldots, 12$) are introduced to ensure the modulation of T in the one-dimensional difficulty. An independent queue is leveraged for each $[A, W]$ to respectively define the initial value and modulate T in a parallel style. Namely, there are 12 independent queues for 12 combinations of A and W. The elements of each queue are used to record T of past trials with the same $[A, W]$. 12 arrays for the 12 combinations of A and W are used to store the success or failure of individual trials. When the i^{th} combination $[A, W]$ is provided for the player in the current trial, the task difficulty and performance of the past trial $\mathrm{Q}_i\,(k-1)$ with the same $[A, W]$ are extracted from the corresponding queue to act as the reference for predicting the T of the current trial $\mathrm{Q}_i\,(k)$.

C. CLOSED-LOOP CONTROL TO OBTAIN THE CONSTANT SUCCESS RATE

To maintain the expected success rate for users, feedback of user performance is necessary for the adaptive algorithm to continuously adjust task difficulty. Here, the real-time success rate is tracked to provide the trial-by-trial feedback of the user performance in each trial. We define a sliding window (with a length of N trials) to observe the real-time success rate η as follows:

$$\eta(k-1) = \frac{1}{N}\sum\nolimits_{i=k-N}^{k-1} S_i \tag{2}$$

where S_i is the resulting Boolean score of the i^{th} trial ($S_i = 1$ for success, 0 for failure). Currently, we use 75% as the target success rate η_{e} of last 35 trials. In addition to the success rate, the actual reaction time of user is also tracked to adjust the allowable reaction time sensitively.

The control flowchart of the DAD model is proposed to obtain the constant success rate for the one-dimensional optimization problem. We take the allowable reaction time in the coming trial (T_{k+1}) as the output variable of the DAD controller to construct the model of DAD. The iterative formula used to compute T_{k+1} is defined in Eq. (3):

$$\begin{cases} T'_{k+1} = T_k + \alpha\,(\eta_k - \eta_{\mathrm{e}}) + \beta\,(\omega T_k - \lambda t_k) \\ T_{k+1} = \begin{cases} T'_{k+1}, & T'_{k+1} > T_{\mathrm{p}} \\ T_{\mathrm{p}}, & T'_{k+1} \le T_{\mathrm{p}} \end{cases} \end{cases} \tag{3}$$

where T'_{k+1} denotes the iterative value of the allowable reaction time for the $(k+1)^{\text{th}}$ trial. T_k denotes the allowable reaction time for the k^{th} trial. t_k denotes the actual reaction time for the k^{th} trial. η_k denotes the real-time success rate of the k^{th} trial. α, β, ω, and λ are the coefficients. T_{k+1} is the final value of the allowable reaction time for the $(k+1)^{\text{th}}$ trial. T_{p} is the basic reaction time of player to achieve η_{e}.

Based on the characteristics of the fingertip force control task, T'_{k+1} in Eq. (3) was adjusted by the following items: the historical allowable time item T_k, the success rate deviation item $\alpha\,(\eta_k - \eta_{\mathrm{e}})$, the reaction time margin item $\beta\,(\omega T_k - \lambda t_k)$, and the basic ability item T_{p}. To maintain a target performance, conventional strategies tend to only take the historical item and the target deviation item into consideration. After a series of pilot experiments, an improved strategy adopting the reaction time margin item is proposed to fully tap the potential of players in each trial. The meaning of each item in Eq. (3) is explained respectively as follows.

T_k refers to the historical information of the last adjustment of the iterative algorithm. Based on the backward propagation approach, T_k is served as the initial value of iteration for the $(k+1)^{\text{th}}$ trial, enhancing the continuity of the adaptive control process.

$\alpha\,(\eta_k - \eta_{\mathrm{e}})$ is the deviation of the real-time success rate η_k from the target success rate η_{e}, where α is a coefficient. Greater the deviation between η_k and η_{e} is, greater the adjustment amplitude of T_{k+1} is. The adaptive step of iteration for difficulty adjustment was used to speed up the convergence to the target success rate.

$\beta\,(\omega T_k - \lambda t_k)$ is the margin of the reaction time between the allowable reaction time T_k and the actual reaction time t_k, whereβ is defined as the scaling factor. The actual reaction time t_k is regarded as one of performance metrics during a session to evaluate and track a user's skill level in real time. The feedback of actual reaction time is taken into account for the closed-loop control to track behavioral fluctuation.

T_{p} is regarded as the lower limit of the reaction time. The aim of T_{p} is to enable the allowable reaction time in each trial is becoming closer to the reaction time required for η_{e}. According to our understanding, if the entry into the target range is considered as one time of successful reaction in the discrete task, the reaction time (T_{ID}) computed by Fitts' Law is the average reaction time required for 100% correct rate under a pair of A and W. Therefore, the average reaction time defined in Fitts' Law is greater than the reaction time of player to achieve the target success rate (i.e., 75%). Regardless of other factors, T_{p} can be taken as the average reaction time to achieve the target success rate after an average margin T_{d} is subtracted from T_{ID}. Accordingly, T_{p} is defined in Eq. (4). The real-time success rate tends to be high or low if T_{p} is too large or too small. In this paper, the value of T_{d} is empirically determined as a small value (i.e., 100 ms).

$$T_{\mathrm{p}} = T_{ID} - T_{\mathrm{d}} \tag{4}$$

However, the difference from the classical task explained in Fitts' Law is that the time consumed by the switch between different fingers should be taken into account in the multi-finger task. Especially, the switch between two fingers from different hands tends to take more time because it involves left and right brain communication. Therefore, T_k is greater than T_{p} in most cases.

Furthermore, t_k in each trial was tracked in real time. If T_k is greater than t_k, this means that the user has successfully completed the force control task within T_k. In this case, it implies the user's force control capability under the current allowable time had more potential for exploitation. To make full use of the potential in the next trial with the same $[A, W]$, a smaller allowable reaction time can be provided according to the margin, and thus to enable the allowable reaction time in the next trial to become closer to user's current capacity of force control.

On the contrary, if the user fails to finish the force control task in the k^{th} trial, the control algorithm would directly set t_k equal to T_k. In this case, T_k is actually set as the upper limit of the reaction time. As mentioned above, the allowable reaction time is greater than the basic reaction time of the person. Under our hypothesis, inattention would be the main reason for the decrease of performance in the current trial. Therefore, we provide the user with the upper limit of the reaction time to create an urgency to focus greater attention on the follow-up trials.

The initial allowable reaction time T_0 in the first trial is determined based on Fitts' Law. As a period of the human adaptation, the initial reaction time for a given task should be greater than the average time specified in the classic Fitts' Law. The value of T_0 is multiplied by an amplification factor ξ for the initial state. Therefore, T_0 is determined in Eq. (5):

$$T_0 = \xi \left(a + b\sqrt{A/W}\right) \tag{5}$$

D. IMPLEMENTATION OF THE CONTROL ALGORITHM

Based on the above analysis, a 2.5% allowable deviation is predefined for the fluctuation of the real-time success rate η in this paper. Therefore, the control goal of this adaptive algorithm is to adjust T to accelerate η to enter the target zone [72.5%, 77.5%] as quickly as possible, and maintain it inside the target zone as long as possible.

Games should be sufficiently challenging, match the player's skill level, vary the level of difficulty, as well as keep an appropriate pace [43]. However, it is not easy to assign appropriate values to these parameters in Equations in Section 4. In our attempts to find out the parameters meeting the design requirements, we referred to the method adopted by Anguera *et al.* [55]. These parameters are empirically determined through extensive pilot testing with the aim to: (1) minimize the number of trial runs until convergence, and (2) minimize convergence instability. According to our experience, it is recommendable to individualize these weights in the subinterval of different success rates. The control algorithm is to automatically adapt the trial-by-trial variation in the user's force control skill.

V. VALIDATION OF THE DAD MODEL

A. PARTICIPANTS

24 participants (9 females, ages ranged from 21 to 31 years, with a mean of 24.1) from Beihang University and Beijing Normal University participated in the validation test. All participants were right handed according to their preferential use of the hand during daily activities such as writing, drawing, and eating. The subjects had no previous history of neuropathies or traumas to the upper limbs. None of the subjects had a history of long-term involvement in hand or finger activities such as typing and playing musical instruments. All participants gave written consent to participate in the study and each of them received a bonus of ¥ 50 (about $ 8 USD) after the whole test was finished.

B. PROCEDURE

24 participants were randomly assigned to one of the two groups, either the test group or the control group. 12 participants in the test group received three training sessions with the improved strategy algorithm. The other 12 participants in the control group received the same number of training sessions with a conventional strategy algorithm. A total of 1200 trials were provided for each participant from the test group. In each trial, the executive finger was randomly assigned by the visual cues. In order to avoid fatigue, the game procedure was subdivided into three sessions and each session consisted of 400 trials. There was a 5-min break between two adjacent sessions. Before the formal experiment, all participants underwent a short practice with 20 trials to get familiar with the apparatus and the procedure of the stimulus-reaction task. All participants were encouraged to use the shortest possible time to obtain as higher scores as possible.

C. RESULTS

Results from the test consisting of 1200 trials show that all 12 participants in the test group achieve the target success rate, i.e. the average value of 75% within about $\pm 5\%$ fluctuation range. Moreover, Fig. 5 shows results from one participant in the study. All real-time success rates of 12 combinations $[A, W]$ are rapidly convergent into an acceptable range from 70% to 80%. This confirms the effectiveness of the DAD with independent queues.

To observe the fluctuation of user success rate from an overall perspective, a different success rate was calculated by using a sliding window of length 35 consecutive trials, rather than considering the 12 pairs of A and W separately. Two typical participants were selected from the test group and the control group respectively as an example. Fig. 6. shows the real-time success rates of two participants during the three sessions. With the help of the proposed IS algorithm, the participant from the test group achieves a more stable real-time success rate fluctuating around the target success rate. This provides an indication of how well the algorithm adapted to user performance, i.e. how well it stayed at the

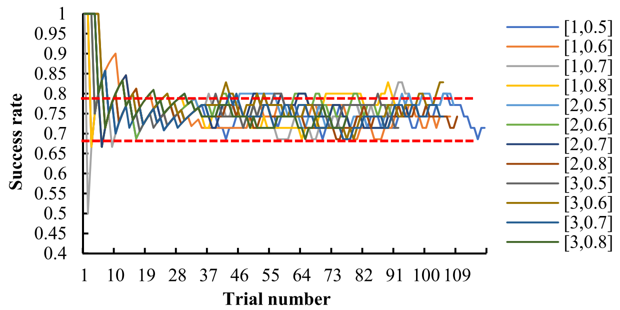

FIGURE 5. Real-time success rates of all 12 pairs of $[A, W]$.

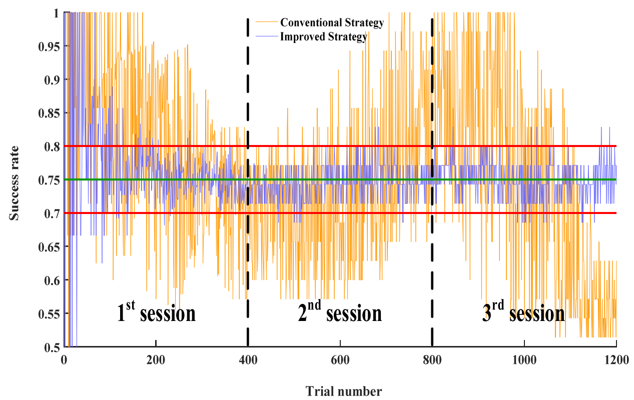

FIGURE 6. Real-time success rates of two participants from two groups.

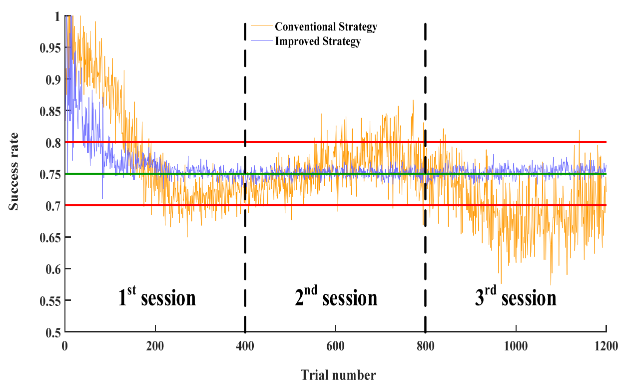

FIGURE 7. Average real-time success rates of all participants in each group.

target success rate of 75%. We can see that for the first 400 trials, the real-time success rate tended to be higher than 75%, but it eventually converged to the target value along with a small fluctuation. Furthermore, the break between the two adjacent sessions has no effect on the real-time success rate because the real-time success rate does not appear a significant jump at the beginning of the second and third sessions.

In addition, Fig. 7 respectively shows the average real-time success rates of all participants in each group. During the whole completed session, the average real-time success rate of participants in the test group enters the acceptable range

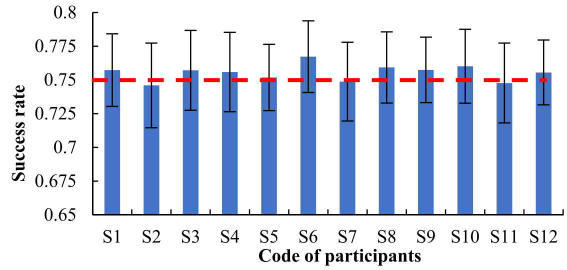

FIGURE 8. Means and standard deviations of success rate in the last 200 trials.

earlier and then is fluctuating around the target success rate with a narrow range of continuous oscillation (i.e., less than 10%) after 100th trial. By contrast, the average real-time success rate of participants in the control group is fluctuating in a wide range and unable to maintain within the acceptable range.

Fig. 8 shows all means and standard deviations of success rates of 12 participants in the test group. All of them maintain the expected success rate 75% within about ± 5% fluctuation range in the final stages of training. Nevertheless, the number of trials to enter the acceptable range of success rate are quite different for each participant in the test group, as shown in Fig. 9. The reasons accounted for this differentiation might be the random cues of $[A, W]$ and the individual difference of participants. The maximum number of trials required for a stable success rate is 146. The success rates of 12 participants in the test group entered and remained in the acceptable range after they experienced a mean of 108 trials with a standard deviation of 31.45 trials. This suggests that the proposed algorithm of DAD possessed a rapid convergence rate for randomized 12 difficulty levels in the force control task.

VI. EXPERIMENT OF ATTENTION TRAINING

A. PARTICIPANTS

24 participants (9 females, ages ranged from 19 to 25 years, with a mean of 22.3) from Beihang University and Beijing Normal University participated in the experiment. All participants were right handed according to their preferential use of the hand during daily activities such as writing, drawing, and eating. The subjects had no previous history of neuropathies or traumas to the upper limbs. All participants gave written consent to participate in the study and each of them received a bonus of ¥ 280 (about $ 40 USD) after the whole experiment was finished

B. PROCEDURE

Participants received detailed information regarding a longitudinal experiment over 7 days span. Schedules were fully explained and were informed of their right to withdraw at any time. If a participant had any questions about the instructions, the experimenter provided clarification. They were further instructed to place equal emphasis on responding both quickly and accurately. To stabilize motivation levels, each participant was clearly emphasized to do their best in all tasks

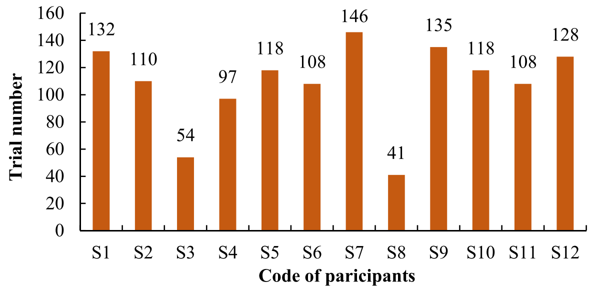

FIGURE 9. Trial number to enter the acceptable range of success rate for each participant in the test group.

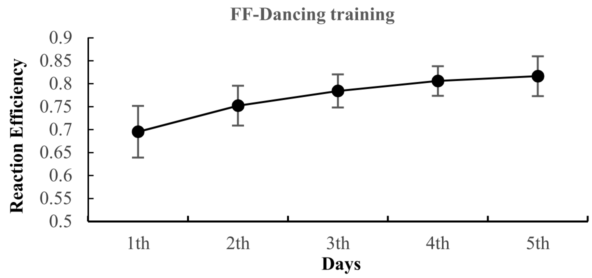

FIGURE 10. Means and standard deviations of reaction efficiency of all participants in training group.

throughout the experiment. In the field of attention, the SART and the Stroop tasks are two classic batteries of attention test often used to evaluate the effectiveness of techniques designed to improve sustained attention. In addition to details of FF-Dancing, the SART and a modified Stroop task (Chinese version) were also introduced for all participants in paper form, as described by Chan *et al*. [16] and Moore *et al*. [17] respectively. All participants provided written informed content after a brief experience of FF-Dancing.

24 participants were randomly assigned to one of the two groups, either the training group or the control group. 12 participants in the training group underwent a computerized test battery of attention including SART and Stroop task. Each of participants repeated the test battery twice (the order of these two testing was counterbalanced) with the interval of about 5 hours on the first day. Then, from the next day, they were asked to play the FF-Dancing for one time per day for 5 consecutive days. On the seventh day they will receive the same test as on the first day. The other 12 participants in the control group come to the laboratory only twice: on the first day and the seventh day for the same tests as the training group. Prior to performing the Stroop tests, every participant has an opportunity to practice freely until he / she could make correct reaction with all involved fingers.

C. MEASURES

A substantial amount of work on improving performance has been done in the context of a continuous-performance task known as the sustained attention to response task [47]. In this task, failures to withhold button pressing to an infrequent no-go stimulus are scored as errors of commission and are used to index sustained attention ability, with more errors indicating poorer sustained attention ability. This is because in the majority of the studies, sustained attention performance was indexed by SART commission errors, but mean response time (RT) data were not included with the mean error data.

An index incorporating both accuracy and reaction time into the assessment of sustained attention performance may be warranted. Using the SART to index sustained attention ability, commission errors are commonly used as an index of lapses in sustained attention. Seli *et al*. [47] found that the commission errors were a systematic function of manipulated differences in response delay. In view of their results, there is some concern that it has not been the norm for researchers who have examined interventions aimed at improving sustained attention performance to report RT changes along with error performance measures. They therefore strongly encourage researchers to report mean RT data in any studies aimed at improving sustained attention performance, so that any possible effects of speed–accuracy trade-offs can be taken into account when drawing inferences from the data. They thought that it is presumably possible for individuals to hold constant sustained attention to a task while shifting along the speed dimension of the speed–accuracy trade-off curve, responding either more quickly or more slowly, depending on the strategy employed by the individual. Another reason for serious consideration of changes in response delay following attentional training is that some or all training methods may well affect sustained attention not directly, as intended by the therapy, but indirectly by modulating response tempo [47]. An "efficiency estimate" was proposed to combine both the accuracy and speed of responding into a single measure [56].

In doing so, the "efficiency estimate" in the SART was calculated as arcsine of square root of the ratio of number of hits by average reaction time on correct response by dividing the number of correct responses per millisecond [56]. Similarly, "reaction efficiency" was proposed to assess the performance in the FF-Dancing and the Stroop task. It was calculated as a ratio of the correct rate by dividing average reaction time on correct response. In this paper, the reaction efficiency means number of effective hits per second.

D. RESULTS

Fig. 10. shows means and standards deviation of the reaction efficiency indexing participants performance from the training group during FF-Dancing gaming. The average reaction efficiency of 12 participants has been increasing gradually over the consecutive five days. Whereas, it seems that the ceiling effect is approaching on the fifth day. The reaction time increases slightly from day 4^{th} to day 5^{th}, but the standard deviation is greater.

Use of the Kolmogorov–Smirnov test revealed that the data followed normal distributions ($P > 0.05$). We then conducted repeated-measures ANOVA with *Time* (pre-test vs. post-test) as the between-subjects factor and *Group* (training vs. control) as the within-subjects factor.

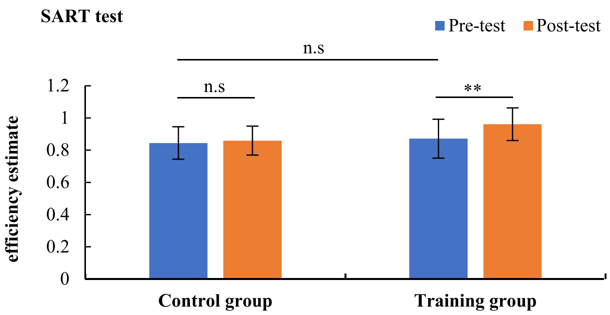

FIGURE 11. FF-dancing training effect on efficiency estimate in SART. (*$P < 0.05$, **$P < 0.01$, and ***$P < 0.001$; n.s., not significant).

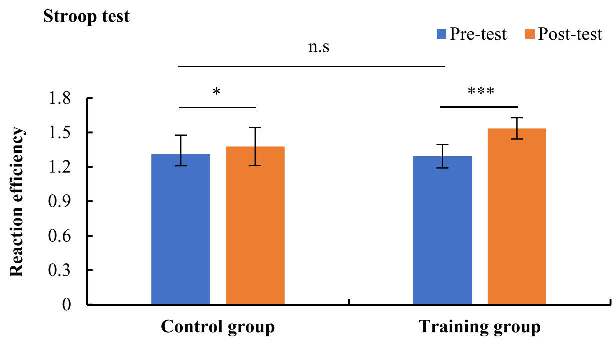

FIGURE 12. FF-dancing gaming effect on reaction efficiency in stroop task. (*$P < 0.05$, **$P < 0.01$, and ***$P < 0.001$; n.s., not significant).

Fig. 11 shows means and standards deviation of efficiency estimate of all participants in the SART task. Participants showed a greater increase in the average efficiency estimate after training with FF-Dancing. Analysis on efficiency estimate revealed a significant main effect of *Time* (F (1, 22) = 9.079, P = 0.006). Interestingly, we found an interactive effect of *Time* × *Group* (F (1, 22) = 4.663, P = 0.042), as *Group* on the efficiency estimate was only evident (F (1, 11) = 9.508, P = 0.01) after receiving training but not before training. This result suggested that participants in the training and control group did not differ in baseline of the efficiency estimate (F (1, 11) = 0.274, P = 0.611). Furthermore, we found that the change of efficiency estimate from pre-test to post-test was only significant in the training group (F (1, 11) = 22.568, P = 0.001) but not in the control group.

Similarly, Fig. 12 shows means and standards deviation of efficiency estimate of all participants in the Stroop task. Specifically, the average reaction efficiency of the training group increased by 18.7%, while that of the control group increased by only 5%. Analysis on reaction efficiency in the Stroop task revealed a highly significant main effect of *Time* (F (1, 22) = 86.963, $P < 0.001$). Moreover, we showed a highly significant *Time* × *Group* interaction (F (1, 22) = 28.887, $P < 0.001$), as *Group* on the reaction efficiency was only evident (F (1, 11) = 6.189, P = 0.03) after receiving training but not before training. These results suggested that participants in the training and control group did not differ in baseline of the reaction efficiency (F (1, 11) = 0.083, P = 0.778). Interestingly, we found that the change of reaction efficiency from pre-test to post-test was more significant in the training group (F (1, 11) = 145.625, $P < 0.001$) than that in the control group (F (1, 11) = 6.203, P = 0.03).

VII. DISCUSSIONS

The convergence of the real-time success rate in the model validation indicates that the proposed model of DAD is able to achieve the predefined success rate and fluctuation range in the force control game. Thus, the first question at the beginning of the first article has been answered. As indicated in Fig. 7, participants achieved and maintained the expected success rate of 75% within ± 5% fluctuation throughout the training controlled by the improved strategy. This result should be attributed to the on-line monitoring and real-time feedback of the closed-loop control strategy. The comparison with the conventional strategy shows that the reaction time margin item is very worthy to be considered in the adaptive adjustment to match the user's capabilities. The experimental results validate that the model of DAD meet the three requirements: tracking the time-varying user's skills, compatible with individual differences, and adaptive difficulty adjustment in the force control task. Additionally, even though the game was paused between two consecutive sessions, inheritance of iterative algorithm gives the player a consistent performance at the beginning of the next session. Compared with our previous method [11], the new adaptive strategy proposed in this paper no longer needs to calibrate the force control skill for the same user before he or she prepares to take this attention training again. However, there are several open issues that need to be discussed.

Admittedly, this is a very time-consuming method, but it is really practical and effective in the absence of prior knowledge and mathematical models for reference. Anguera *et al.* [55] developed a video game training for cognitive control enhancement in older adults. In the video game, an adaptive staircase algorithm was used to determine the difficulty levels of the game at which each participant performed the perceptual discrimination and visuomotor tracking tasks in isolation at about 80% accuracy. Parameters of the adaptive algorithm were chosen following extensive pilot testing to: (1) minimize the number of trial runs until convergence was reached and (2) minimize convergence instability, while (3) maximizing sampling resolution of user performance [55]. Using the same method, we also empirically tuned several design parameters in the DAD approach after extensive pilot experiments. It should be noted that the 75% success rate may be not the optimal performance level leading to effective training for these parameters.

As a novel attention training game, the optimal dose of training and categories of attention engaged in the FF-Dancing are two remaining problems required to be solved in the future. Individual difference is a factor that cannot be ignored in attention training. Individual difference has an influence in the baseline of finger force control skill, as shown in Fig. 9. In Fig. 10, the greater standard deviation can also be attributed to the individual difference. Compared with the 4^{th} day, reaction efficiencies of several participants had stopped growing, or even worse, while others' reaction efficiencies continued to grow on the 5^{th} day. Five days of FF-Dancing training may be enough to reach the ceiling of some participants' abilities who showed a decline in performance, while more training is required for others. Different doses of training are needed for different attention training tasks [5], because video game playing affects the brain at multiple time-scales [48]. Some effects occur after small amounts of training, whereas others require extensive practice. Moreover, some behavioral training tasks and testing tasks may target one or a combination of the following cognitive domains: focused attention, sustained attention, selective attention, alternating attention, and divided attention [57]. There is a consensus in assessing the sustained attention by SART (a typical continuous performance test, CPT) [56]. Nevertheless, there seems to be still controversy in the categories of attention that Stroop task could assess. The Stroop task has been used to assess the selective and divided attention [58], [59], as well as executive attention in meditation [60], [17]. Therefore, extensive follow-up studies are necessary to determine the type of attention invoked in FF-Dancing.

In the Stroop task, the growth of 5% in reaction efficiency from pre- to post-test could be accounted for by possible learning effect in the control group. Schubert and Strobach [61] speculated that the learning effect between pre- and post-test sessions is probably caused by task repetition rather than training. Compared with the control group, the greater growth of reaction efficiency from pre- to post-test can be attributed to task training in the training group because no significant difference in the reaction efficiency is shown between the two groups in the pre-tests ($F\,(1, 11) = 0.083$, $P = 0.778$). However, the learning effect has not been found in the pre-tests of SART. The alternate use of four fingers is more likely to be the root cause of learning effect. As described by Moore *et al.* [17], compared with simply clicking using only a finger in the SART, reactions to stimuli in the Stroop task involve an accurate switching between four fingers (index and middle fingers on both hand). The results from Furuya *et al.* [62] provided evidence for the enhancement of individuated finger movements through dexterous hand use during piano practice. That those effects are indeed learning effects is underscored by the fact that they are seen not only on retention tests without focus instructions or reminders, but that they transfer to novel situations [63]. Mack *et al.* [19] thought that an examination of purely attentional effects must therefore use a paradigm without any motor involvement. Indeed, motor behavior is subject to a variety of social-cognitive-affective influences [64].

Some studies support a proposition that an external focus speeds up the learning process, thereby enabling performers to achieve a higher level of expertise sooner [63], [65]. As reviewed by Wulf [63], the enhancements in motor performance and learning through the adoption of an external relative to an internal focus of attention are now well established. Correspondingly, the converse of this proposition is whether force control task could speed up attention-related brain activation, thereby enabling performers to achieve a higher level of attention engagement. The learning effect is indeed inevitable in this unresolved inverse problem. While, the learning effect induced by motor control is a difficult to cope with but critical challenge in attention training involving force control tasks. Aside from learning effect, we also need to control for other subject-related noise factors such as users' preferences and fatigue.

Targeting the inverse proposition, this paper demonstrates that finger force control as described in the FF-Dancing can facilitate attention improvements in the SART and the Stroop task. Therefore, the second question at the beginning of this article has also been answered preliminarily. Future research will hopefully explore the behavioral and neurophysiological explanations behind the findings. Specifically, we will elucidate how brain activity changes and what behavioral and neural markers can effectively index real-time attention state during FF-Dancing gaming. Zentgraf *et al.* [66] found higher activation in the primary somatosensory and motor cortex for an external focus (on keys) relative to an internal focus (on fingers). Whether or not this activation pattern was specific to the (tactile) nature of the task is an open question. It remains unknown how well participants were attentive from moment to moment during playing in the present experiment. With behavioral and neural markers of attention in the FF-Dancing, the fluctuation of moment-to-moment attention state could be monitored. Whereby, it is possible to reveal neural mechanism of attentional plasticity under modulation of force-control tasks. By observing neural signals during the attention training process, closed-loop training with real-time attention detection could be developed to activate attention at an adequate level for a relatively long time. As a result, the FF-Dancing may be an appealing tool to boost attentional control and in turn performance in perceptual or cognitive tasks, opening a new window on how to foster learning and brain plasticity in the context of haptic interaction [67].

VIII. CONCLUSIONS AND FUTURE WORK

In summary, we have introduced a control strategy for adaptively adjusting the difficulty of an immersive visuo-haptic attention training game using finger force control. With the dimension reduction approach, an adaptive model of the allowable reaction time is proposed to achieve online adjustment of the difficulty level during FF-Dancing playing, and thus to match the difficulty level to a user's force control capability. Experimental validation indicates that the adaptive model is able to obtain and maintain the target success rate, i.e. the average value of 75% within about $\pm$ 5% fluctuation range across all participants. FF-Dancing is well-tolerated by different participants due to its adaptability to uncertain fluctuations in user performance and individual difference in the fast-paced stimulus-reaction force control task. After five days of longitudinal training experiments, the efficacy of intensive FF-Dancing gaming on attention training is validated by using two typical attention tests (the SART and the modified Stroop task). This study confirms that FF-Dancing can facilitate attention improvement of trainees and be an effective attention training game with haptic interaction.

In the next step, neuroimaging methods such as EEG or fMRI measurement will be employed to reveal the underlying behavioral and neural markers of attention during FF-Dancing gaming. A challenge for this future research will be to disentangle these potential influences of learning effect in the attention measurement. If successfully overcome the challenge, we will be able to develop a closed-loop neurofeedback approach for attention training using the FF-Dancing. These studies may promote our understanding in mechanisms and applications of haptic interaction in fostering learning and brain plasticity.

ACKNOWLEDGMENT

The authors would like to thank Peng Ye, Qiqi Guo, and Hongyu Chen for help with software support and subject recruitment.

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