Real-Time Stealth Intervention for Motor Learning Using Player Flow-State

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***Abstract*— We present a novel approach to real-time adaptation in serious games for at-home motor learning. Our approach assesses and responds to the "flow-state" of players by tracking and classifying facial emotions in real-time using the Kinect camera. Three different approaches for stealth assessment and adaptation using performance and flow-state data are defined, along with a case-study evaluation of these approaches based on their effectiveness at maintaining positive affective interaction in a subject.**

Keywords—serious games, autonomous training, stealth adaptation, flow-state evaluation, affective design

I. Introduction

Affective interaction has played a central role in the development of smarter, richer gameplay in serious games. When a game is aware of a player's emotional state, on-the-fly adjustments can be made to provide the gameplay experience most beneficial to that player, either to avoid a negative outcome or to augment and improve positive outcomes. In this work, we apply affective serious game design to facilitate motor learning, where the user interacts with a game environment to acquire or improve a particular motor skill.

In motor learning, as in many other fields of learning, maintaining a learner's positive and engaged emotional state is a key element in the learning process. Physical trainers are well aware of this fact as they constantly respond to the emotions expressed by their trainees during exercise. For example, if a trainee exhibits signs of fatigue, the trainer may adjust the intensity of the motor exercise to allow the individual to recover. However, trainer availability is greatly limited. As in cases like rehabilitation, the frequency of exercise required by an individual to maintain steady improvement over time far exceeds the trainer's availability, increasing the need to augment programs with at-home training.

This disparity has given rise to a variety of research solutions for automated motor training. In the serious games field, solutions were developed for at-home settings using commercially available hardware like the Nintendo Wii remote due to the importance of cost-effectiveness. A prominent early example is the work by Alankus et al. [4], who emphasized the need for customizability in these interfaces to facilitate a wide variety of rehabilitative conditions and player interests. Deutsch et al. [5] further simplified this approach by applying a commercially-available Wii game (Wii Sports) as a mechanism for motion training targeting adolescents with Cerebral Palsy.

The more modern Microsoft Kinect sensor gained heavy popularity in many approaches due to its non-invasiveness and ability to track full-body motion and joint data in real-time, making it ideal for rehabilitative therapy [6]. Progress toward customizable motion training and evaluation has been made using Kinect data and techniques like Dynamic Time Warping (DTW), which scales time-series motion data for comparative analysis [7]. Several other recent studies have validated the Kinect as a rehabilitative device [1, 2, 3]. Despite many advances in motion tracking in this field, there remains one major component in motivating and engaging players: real-time affective interaction. Affective interaction is important to maintaining long-term player engagement [8]; a non-invasive approach to emotive tracking and intervention, which can integrate with already available commercial hardware like the Kinect and Wii devices, is crucial to its implementation in motor learning.

Therefore, we propose a solution to facilitate guided at-home motor training using an automated serious gaming system. To provide the quality of training experienced with a live trainer, we propose affective interaction using stealth assessment and adaptation. In Section 2, we provide an overview of related work in the fields of affective games, motor learning, and stealth assessment. In Section 3, we introduce our approach to motor training: the Autonomous Training Assistant. We discuss in detail how we can link facial emotive state to flow-state in Section 4, and describe our approach to stealth adaptation in Section 5. In Section 6 we present an evaluation of three adaptation techniques using flow-state as a metric, and compare the techniques to a control condition in which no adaptation is implemented in gameplay. We discuss our conclusions and directions for future work in Section 7.

II. Related Work

Research on affective design in serious games has covered many different approaches to detection, response, and regulation over the past two decades, with a broad range of applications. Here we describe some of the most popular

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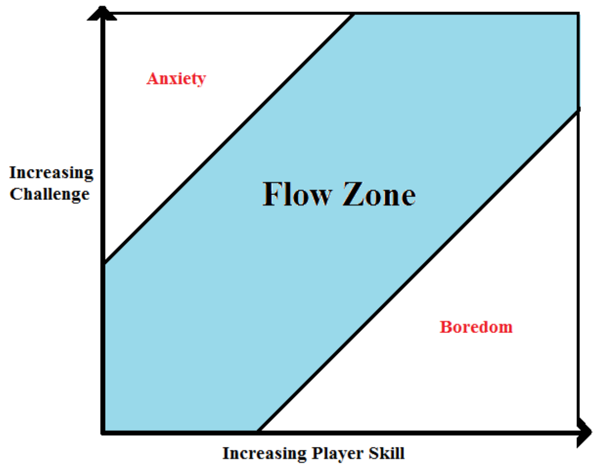

Fig. 1. Flow-State Diagram

general approaches to achieving affective interaction in these games.

The first step of the process is detection. To detect affective state requires that a game interface is able to capture visual or physiological data in real-time and to interpret and classify this data. Many different techniques have been developed to extract this data in real-time. Sykes and Brown [9], for example, measured emotion through the exertion of pressure on a game controller. Sourina and Liu [10] explored the use of EEG as a measure for emotional state assessment. Jennett et al. utilized eye movements, task completion time, and even subjective methods like questionnaires to determine affective response in players [11]. While no particular method has a clear advantage, the key is to consider the usage scenario and learning context to determine which method to use when extracting emotional data.

The next step is classification. Once emotional data has been read by the system, it must assess the emotional state of the player using a metric. Perhaps the most popular metric is "flow-state". The concept of "flow" was coined by Mihaly Csikszentmihalyi in 1990 [12]. In serious games, as discussed by Jenova Chen, "flow" represents the emotional state in which a user is engaged and sufficiently challenged by the gameplay scenario, and is neither bored due to lack of stimulation or frustrated due to excessive difficulty of the game task [13]. Figure 1 demonstrates this concept by mapping increasing player skill to increasing levels of challenge in game content. The range in which the game's progression of challenge meets the player's increasing skill level is the "flow zone"; optimally-designed serious games maintain this zone of proximal development throughout a player's experience.

Several techniques have been proposed in research to detect and maintain flow-state. Nacke and Lindley, for example, linked subjective and objective indicators by noting the correlations between physiological data like EEG and ECG with subjective responses indicating flow-state in questionnaires to determine various configurations in first-person shooter games that help maintain flow-state [14]. Other measurements, like heart rate and electrodermal activity, have been correlated with flow-state as well [15]. Often, however, these techniques are intrusive and the mechanisms for detection may interfere or distract from gameplay, which is particularly undesirable in the realm of motor learning. To this end, less intrusive techniques using computer vision have proven useful. Tan et al. have demonstrated, for instance, that facial emotion recognition from video sources can allow a system to determine flow-state in real-time during gameplay [16].

To facilitate flow in its design, a serious game can either react to a user's emotional state (reactive approach) or try to evoke a particular emotive state (proactive approach) using various adaptation techniques. Affective games can respond to emotional state in various ways by providing assistance, challenges, or evoking a particular emotional response as necessary [17]. Johnson and Wiles noted that effective user interface design in serious games can help maintain flow-state in fully engaged users [18]. Yannakakis et al. found that camera control may also have an influence on affective state, as a restricted camera view may cause frustration and negatively impact game performance and outcomes [19].

Perhaps the most effective approach has been the adjustment of difficulty in real-time based on a player's flow-state. Liu et al. [20] estimated anxiety levels in players as a measure of flow through physiological input, and responded to this input with Dynamic Difficulty Adjustment (DDA) in real-time. Chanel et al. [21] applied emotional recognition to Tetris through both physiological and self-reported data to indicate that static difficulty resulted in player boredom, and proposed that real-time modulation based on this data would help maintain flow-state to improve the player experience. More recent findings indicate that while the use of psychophysiological metrics alone does not offer an accurate adaptation strategy, combining this data with task performance provides a much more accurate adaptation platform [30, 31]. Furthermore, an effective adaptation strategy can significantly extend the amount of time a user is willing to invest in a training session [32]. This is especially the case when the task's difficulty matches the severity of impairment of the player [35], which favors a person-centered approach. While it is possible to reduce the complexity of this system by including the therapist/trainer as the human-in-the-loop as shown by Aranha et al. [33], this is not always feasible in practice due to limited availability of these professionals. Finally, the link between perceived challenge from engagement and learning outcomes are well established in the literature [34].

Within the affective gaming field, computational models for the measurement of flow in affective interaction are constantly under development. Sharek and Weibe computed flow-state by differentiating between live gameplay and intermission periods, and measuring the number of clicks on a game-clock during each period [22]. Computation of flow using affective data including player emotion is largely unvalidated. A study by Craig et al. [23] demonstrated how this mapping can occur for basic emotions, but the links between this information and the change in an individual's performance over time is yet to be explored.

In the academic learning field, Shute [24] has proposed the concept of "Stealth Assessment" as a means of measuring student performance in academic proficiency goals directly through performance in gameplay. The idea behind stealth assessment is that game tasks can be designed to measure and track a user's learning in a particular subject material. The application of this approach toward flow-state assessment, in combination with non-intrusive machine learning techniques for facial emotion recognition, is the subject of our work.

III. Approach

We propose a novel approach for the application of research in affective game design to at-home motor learning. Our system, the Autonomous Training Assistant (ATA), is a serious gaming environment designed for guided motor learning. The system consists of a rod-shaped input device called the Intelligent Stick containing an accelerometer and vibro-tactile motors for motion detection and haptic feedback, respectively, a Kinect camera for real-time body-tracking, and a serious gaming interface which presents the player with game tasks which measure performance of a specific motor task.

In previous work, we describe our framework for real-time assessment and multimodal feedback on motor tasks using data from real physical trainers and the combination of the Intelligent Stick and Kinect as input devices [25]. To summarize, the system assesses motor performance by fusing accelerometer data and Kinect postural data of a user's motion in real-time, and compares this fused data against a template for ideal performance in two temporal categories and one spatial category. For each category, once the user's performance deviates from the ideal value by a certain threshold (the "tolerance threshold"), feedback is given in one or multiple of three different modalities (audio, visual, haptic) to guide the user. This feedback is intended to parallel the real-time augmented feedback that a physical trainer would give during live training.

In addition, we've designed several game prototypes to implement the guided training. For example, Figure 2 shows one such prototype. In this scenario, the width of the racetrack represents the trajectory requirement of a motor task, while the sharpness of a turn and the smoothness of the user's steering represent the speed and postural requirements of the motor task, respectively. These parameters are adapted in real-time; if a user is performing above the expected level of performance at the motor task, subsequent turns on the racetrack become sharper, narrower, and require more precise steering. Similarly, low performance results in a wider track and easier turns. Since motor performance is directly measured in gameplay and reflected within game outcomes (poor performance results in the car going off the track, for example), the user is able to self-evaluate to improve performance in the same manner that we naturally interact with our environment in the real world, facilitating an improved motor learning experience inspired by the Stealth Assessment technique proposed in [24].

In this work, we propose the addition of real-time flow-state assessment to this system. This is necessary because motor performance alone is insufficient information for a system to determine how well an individual is learning during

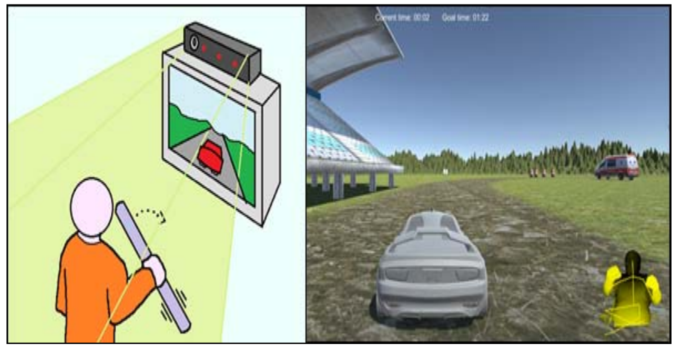

Fig. 2. ATA Overview (Left) and Sample Game Interface (Right)

the experience. A real trainer, for example, would observe and react to an individual's emotional response as well, including boredom and frustration. These can be measured within game design through flow-state recognition.

Here, we determine flow-state externally through facial emotion recognition. This approach was introduced as a bridge between affective state and learning by Craig et al. in 2008 [23], and has since been validated as a feasible real-time metric [16] and applied toward affective analysis in serious games [27] and programming learning [29]; in this study, we apply the approach to motor learning and focus on the interaction between affective state as measured through facial action unit detection and dynamic difficulty adjustment.

A. *Measuring Flow through Facial Tracking*

To receive facial data, we utilize Kinect video data as non-intrusive input data. We process this data using Visage facial tracking [26] in a similar method to [27]. The Visage framework detects human facial features in real-time from the Kinect feed and forms a belief value in each of the six basic human emotions (happiness, sadness, anger, fear, surprise, and disgust) using the Facial Action Coding System (FACS) as described in [28]. It represents its belief state as a value between 0 and 1 for each emotion to indicate how strongly it believes that the user is currently expressing that emotion. This is illustrated in Figure 3. These six values from FACS can then be mapped to affective state as shown by Craig et al. [23], effectively creating a flow-state recognition engine.

As shown in Figure 1, three possible flow-states can occur: boredom, flow and anxiety. We adopt the mapping in [23] and [27] as follows: boredom can be mapped to the state in which all six emotion values are significantly low (directly related to the neutral expression in FACS). Anxiety requires significantly high levels of anger and significantly low levels of happiness, and flow can be linked to high levels of surprise with low levels of sadness. Any other configuration of Visage's data can then be represented as a fourth "other" state to which a game will not react as it is deemed irrelevant in flow-state assessment. As these calculations are done in real-time, the system can also track a player's flow-state over the course of a game experience, thus allowing for adaptation and interaction.

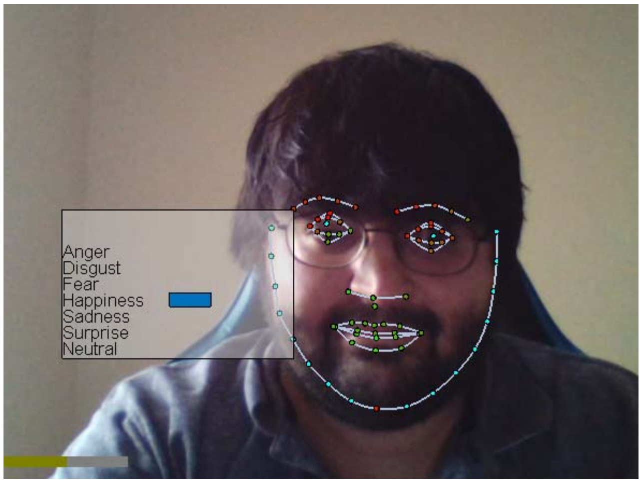

Fig. 3. Visage Emotion Recognition

Several limitations to this approach are worth nothing. One such limitation is that poor tracking may result from a user's facial positioning or by external features which occlude the face including sunglasses. Another is that external stimuli may affect a user's emotions. A user may, for example, react to the temperature in the room, which the system might capture as an incorrect emotion for flow-state assessment. Perhaps most importantly, facial expressions provide only a rough estimate of the user's flow state, and the accuracy of this mapping strategy requires far more validation in research before it can be considered a reliable method for real-world use. We adopt this strategy nevertheless as it is a highly nonintrusive method for measuring affect, requiring no additional wearables to detect physiological input as done in [14] or [15]. This is critical in at-home rehabilitation wherein systems that require complex setup are often deemed inaccessible. Furthermore, we validate this method of flow-state recognition in our own system by comparing player performance to flow-state in the study below.

B. Stealth Adaptation

Using the above approach, our system records motor performance data and emotional feedback data in real-time. The system uses this data to make informed decisions about how to fine-tune gameplay to the user in real-time, just as physical trainers do in live training. Affective information also represents how well the system maintains player engagement. We implemented three adaptation approaches (hit-rate stabilization, Bayesian Network analysis, and k-means clustering classification) in our system as described below:

Hit-rate stabilization: This approach relies on a player's overall rate of success, or "hit rate", at completing a motion objective. For a given motor task, a component of the game is mapped as evidence of completion for that task. For example, a player may be required to rotate the elbow to turn on a race track. In such an example, turn sharpness might correspond to the degree of rotation needed. By rotating to the required degree, the player can successfully navigate the turn. A game may learn this value over a session by recording the player's hit-rate on each objective, where a "hit" is a successful attempt at the objective. The game can then adjust difficulty in real-time until a targeted hit-rate is reached. This approach is based partially on work in [36], although simplified in comparison for computational efficiency in our case.

Bayesian Network analysis: In this approach, the game maintains prior beliefs about player mastery in several components of the task (for example, speed, posture, or motion trajectory). As in hit-rate targeting, the proficiencies are mapped to the game components designed to provide evidence for their completion. Belief states are regularly updated to maintain an up-to-date player model in the game's back-end. Difficulty is then adjusted in each individual component of gameplay based on the belief state relating to that component. This is based on an approach by Shute et al. [37].

Clustering classification: This approach classifies players within performance groups (clusters) based on performance over time using multiple indicators. Often, log data capturing player performance is used to extract the indicators for this clustering. In motor tasks, for example, log data can provide information including motion stability, task completion time, motion trajectory, degree of motion, posture, and more. A player's cluster indicates his or her proficiency at the motion task, and is used to set appropriate difficulty parameters for that player. This approach is based partially on [38].

It is proposed that flow-state ratio can serve as a valuable metric for the assessment of these adaptation techniques. A user's flow-state ratio represents the portion of an active time period during which that user is experiencing flow. A perfect design, as an extreme example, would theoretically yield a flow-state ratio of 1, implying that users were entirely in flow. These techniques are compared in this study using this metric.

IV. Evaluation

A. Design

Due to the high individual variability in motor impairment, motor ability, physical build, and other factors, motor learning is arguably a person-centric process. Despite this, rehabilitative research often treats the subject as a static entity in both design and evaluation. To address this issue, we opted to utilize a case study in which a single participant was observed. To compare the influence of the above three learning approaches on flow-state and performance, we conducted an at-home evaluation of the ATA system in the home of the subject in our case study from [25]. As this is a case study, there can be no generalizable claims made about the effectiveness of the adaptation approaches utilized; rather, we sought instead to determine how well flow-state in each method relates to difficulty parameters as well as player performance under the individually-tailored design introduced in [25]. This study and the procedures below are also detailed in [41].

In this evaluation, the subject's trainer assigned a horizontal stick motion exercise for completion. This task required the subject to swing the "Intelligent Stick" device in a diagonal plane from the lower-right of the body near the waist to the upper left shoulder using both arms. This arc trajectory includes three critical points in 3D space allowing a minimum

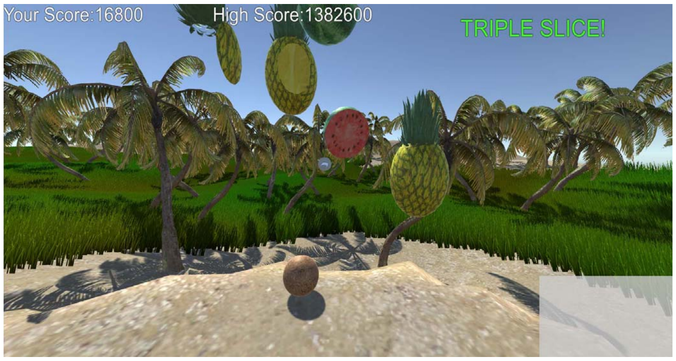

Fig. 4. Fruit Island game prototype.

and maximum trajectory deviation of 5cm and 10cm, respectively, with a minimum and maximum swing rate of approx. 6cm/sec and 9cm/sec, respectively. The trainer also required the subject to maintain a steady lower body during motion, allowing a minimum and maximum deviation of 5 degrees and 10 degrees, respectively. The trainer assigned these values as baseline parameters.

To map gameplay to these parameters, the Evidence-Centered Design (ECD) and stealth assessment techniques in [24] inspired the game's design. We designed a fruit-slicing game based on Halfbrick Studios' Fruit Ninja series based on subject interest from a pre-interview. The subject uses the Intelligent Stick device as a virtual sword to slice fruit which is tossed in the air at regular intervals. The "Island Fruit" game depicted in Figure 4 was designed using the following models:

Competency Model: The user's competency is measured in three categories: trajectory (how closely a user's motion matches the ideal trajectory in space-time), speed (rate of motion and its proximity to the ideal value), and posture (proximity to the ideal body posture during a task).

Task Model: The task requires the subject to contact three critical points in space while maintaining steady lower body posture. This is matched to the task of slicing fruit, where each fruit object represents a critical point, their speed in the air represents the rate of motion required, and the steady motion of the virtual sword requires that the postural requirement is met.

Evidence Model: Evidence of two categories (trajectory, speed) can be observed in the virtual sword's contact with fruit. Each fruit object's center is a critical point, while its radius represents the tolerance range in which a motion may be considered "correct" even if it missed the critical point. This enables both coarse-grain (hit or miss for each fruit object) and fine-grain analysis (proximity of contact point to the center of the fruit). The postural requirement is embedded within gameplay as follows: should the individual lose the required posture, a "balance fault" event occurs in which the virtual sword wobbles, causing significant deviations from the ideal trajectory.

Flow-state ratio was captured using the Visage face tracking library for the Unity platform. In each frame, the skeletal data on the face from the Kinect is used to estimate the subject's emotional state in the six basic emotions (anger, disgust, fear, happiness, sadness, surprise). The tracking system returns a value from 0-1 in each category representing the likelihood that the user is expressing that emotion. For example, a belief output of (0.09, 0.05, 0.11, 0.75, 0.03, 0.24) suggests that the subject is likely to be expressing surprise and happiness, and less likely to be expressing other emotions.

We estimated a user's flow-state using Visage emotion-vectors and a threshold constant *Ft*. The following rules were used to determine the subject's state, using a strategy similar to [23] and [27]:

- If all emotion estimates are below *Ft*, the user is likely in the "boredom" state depicted in Figure 1.
- If the "anger" value is above *Ft* and "happiness" is below *Ft*, the subject is likely experiencing "anxiety" as depicted in Figure 1.
- Otherwise, if the "surprise" value lies above Ft and the "sadness" value lies below Ft, the subject is experiencing flow.
- If none of the above are true, the subject is in an unknown state labelled as "other".

A threshold value of *Ft* = 0.25 was derived from pre-evaluations performed within the research team, but the optimal value of this threshold remains a topic for future research. Adaptable parameters of the game's difficulty included fruit size, fruit motion rate, and error tolerance for lower body motion.

After a brief 1-minute tutorial in which the subject was introduced to the game's controls, the subject participated in four separate 5-minute sessions, with ten-minute breaks inbetween to help alleviate learning effects across conditions. These sessions included a control condition in which no stealth adaptation was used, and three adaptation conditions, Bayes-Net, Cluster, and Hit-Rate, as described below:

Bayes-Net: The subject's proficiency in posture, trajectory and speed were assessed independently using a Bayesian network. Trajectory was estimated as proximity of the virtual sword to the center of a fruit object during contact, speed was estimated as the rate of motion of the virtual sword, and posture as the average angle of the subject's torso relative to the ideal posture over a single swing. In all cases, non-contact with fruit objects was treated as an error. The belief network estimates proficiency in each category and updates these estimates between each swing attempt. Difficulty is also adjusted independently in each category (i.e. if trajectory mastery is poor relative to speed and posture, then only the fruit size is changed).

Cluster: Posture, trajectory and speed are treated as dimensions in a clustering space. Performance values for these categories over a single swing form a 3d data-point. Three clusters representing low, average and high player performance are formed after at least three swings are completed, using k-means for assignment with k=3. From then on, all difficulty parameters are adjusted based on the user's performance cluster. Three pre-defined "levels of difficulty" were set by the subject's trainer, with parameter vectors of (10, 6, 10), (7.5, 7.5, 7.5) and (5, 9, 5) in the format of (fruit size, fruit speed, balance threshold). If the user's swing enters a "high performance" cluster, the difficulty is increased, and vice versa.

Hit-Rate: This method does not evaluate performance at the level of individual categories (posture, trajectory, speed). Instead, it simply observes the total number of fruit sliced by a user per swing. In this instance, three fruit are deployed on each interval (representing three critical points) and the targeted hit-rate assigned by the trainer was two fruits per swing. If the user hits all three fruit pieces in a single swing, difficulty parameters are increased by a constant value (pre-determined by the subject's trainer) until either the user reaches two hits or the maximum difficulty value (again, determined by the subject's trainer prior to deployment) is reached for all parameters. In this case, the subject is considered to have mastered the exercise. If the subject only hits one or less fruit on a single swing, difficulty parameters are lowered until the minimum trainer-assigned values are reached or the user hits the expected two fruit objects on a swing.

Flow-state Adaptation: In all conditions listed above, the subject's emotional state is estimated by the Visage tracker in real-time. For each swing, an estimate of the user's flow-state is made based on the rules given above. Should the user be in the "anxiety" state, the difficulty of all parameters is lowered by a constant amount pre-defined by the trainer in addition to the adjustments made using the base learning technique. Similarly, the difficulty is increased if the game detects "boredom".

In each timed session, the subject was asked to complete as many swings as possible while maintaining comfort standards set by the trainer. Scoring was implemented as follows: on a spawn interval, a single fruit slice yields 200 points, two slices yield 600 points, and three slices yield 1200 points. Emotional information was sampled on each frame using the Visage framework, and a single average was formed for every 10-second interval which was output as a 6-dimensional emotion vector, ultimately yielding 30 vectors for each 5-minute session. Flow-state ratio is the portion of these vectors which represent flow-state using the above roles.

To determine the validity of our approach for the measurement of flow in this study, we also captured the subject's performance over each session by measuring error in the stick's position at each 10-second interval as well as total fruit sliced over the session. The goal was to determine whether the adaptation strategy which yielded the highest flow-ratio also yielded the highest performance (lowest error-rate) compared to control conditions from previous sessions with the subject as well as in comparison to the other adaptation strategies.

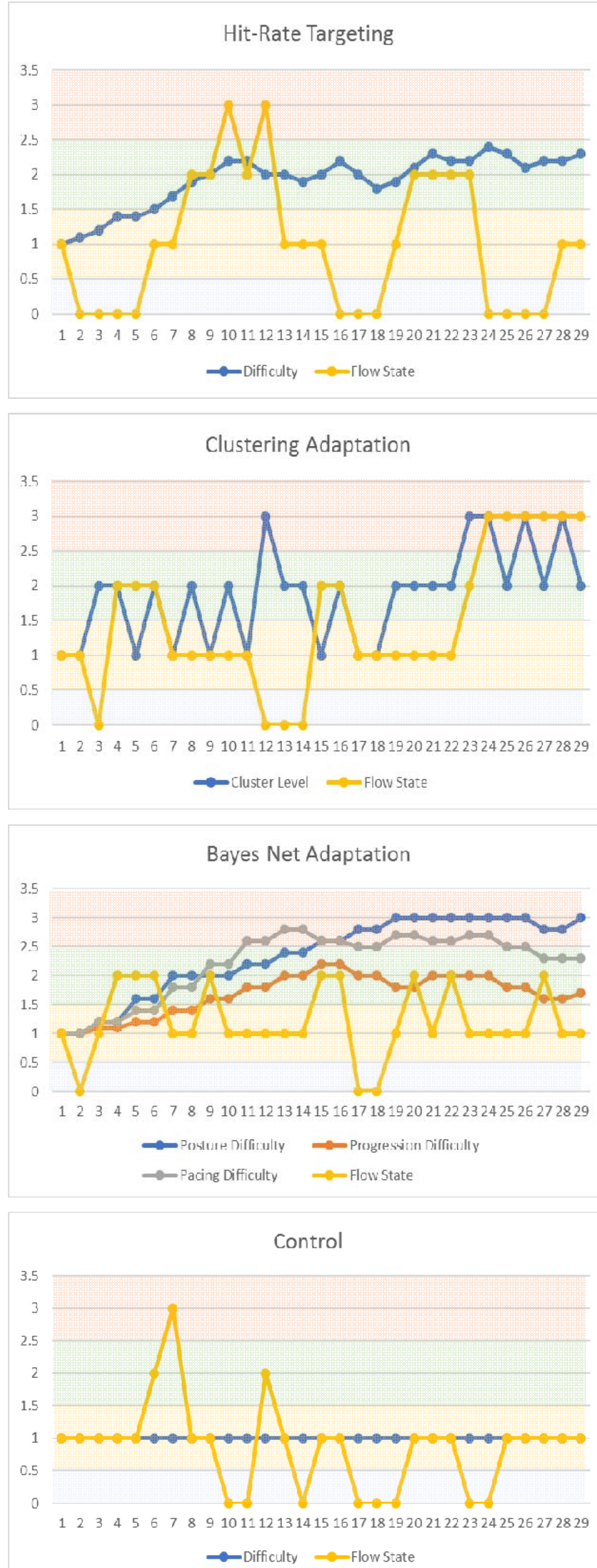

Fig. 5. Flow-state progression values for case study subject.

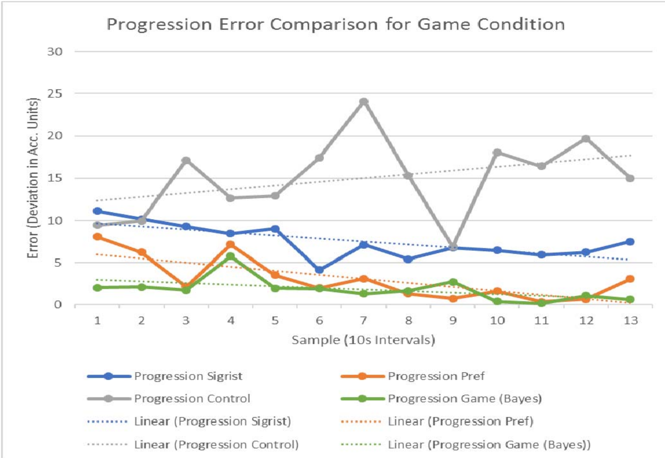

Fig. 6. Error comparison for game condition over 2-minute session.

B. Results

Figure 5 displays flow-state data for each approach. Each data-point is a flow-state measurement sample taken at each 10-second interval over a 5-minute session. Green regions represent flow, while red, yellow and blue regions represent anxiety, boredom and unknown state, respectively. The Bayesian-Network approach yielded the highest flow-state ratio of 0.300, followed by Hit-Rate Stabilization at a ratio of 0.233, and Clustering at 0.200. All three adaptation approaches beat the control approach (no adaptation), which yielded a flow-state ratio of 0.067.

In a previous study [39], the subject completed a similar motion task over 5-minute sessions with the use of a simple training interface (no gameplay), and was given multimodal feedback in three different conditions: one in which no feedback was provided (the subject simply attempted the exercise over 5 minutes with no visual or auditory interface and no haptic feedback from the Intelligent Stick), and two in which multimodal feedback was present (a preference condition in which the subject chose how feedback was received, and one in which the mapping of feedback was chosen based on work from Sigrist et al. [40]). Error values for these three sessions were captured in 10 second intervals and were measured by the distance between the stick's actual position and its optimal position at each time sample. The error values for these sessions are compared with the Bayes Net adaptation condition in Figure 6. Trend lines for each condition are shown. The game condition yielded the highest reduction rate for user error (and hence, the greatest improvement in performance) over a gameplay session. For the Bayes adaptation condition, the subject also performed the highest over all other adaptation conditions with a value of 62 total fruit sliced in comparison to 47, 46 and 51 for hit-rate targeting, clustering, and control, respectively.

V. Conclusions and Future Work

While the results of this case study evaluation cannot be deemed generalizable at this stage, the observed relationship between flow-state ratio and error-rate in the results above help validate the use of facial expression tracking during gameplay to establish flow in the player. This is critical in the motor learning domain where individual variability is inevitable. When combined with the methods described above for stealth assessment and adaptation, our novel technique for real-time flow-state analysis and adaptation in exergames yields affective game design that is more responsive to an individual's state in at-home unsupervised training. The healthcare and rehabilitative domains, with physiotherapists who are highly responsive to both subject performance and affective state, are a natural fit for autonomous home training, although applications to other motor learning domains may be considered in future studies.

To determine the relative advantage of this flow calculation strategy more conclusively, an in-depth study including multiple threshold values for flow-state determination over a longer period with multiple subjects is necessary. Furthermore, it may be beneficial to determine the relative interaction between performance adaptation and affective adaptation, as this was not covered in the current study. A long-term evaluation comparing the adaptation methods used in this study on multiple users with varying levels of both motor ability and game experience would help determine which has a stronger effect on flow-state in various contexts. Furthermore, a broader evaluation encompassing multiple game designs would determine the generalizability of these approaches across varying subject profiles. These evaluations and the development and refinement of alternative adaptation techniques for motor learning can aid in the design of smarter, more effective serious games in the rehabilitative space.

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References

[1] P. J. Chen, Y. C. Du, C. B. Shih, L. C. Yang, H. T. Lin, and S. C. Fan, "Development of an upper limb rehabilitation system using inertial movement units and kinect device," in 2016 International Conference on Advanced Materials for Science and Engineering (ICAMSE), 2016, pp. 275–278.

[2] M. Demers, D. C. C. Kong, and M. F. Levin, "Acceptability of using a Kinect-based virtual reality intervention to remediate arm motor impairments in subacute stroke," in 2017 International Conference on Virtual Rehabilitation (ICVR), 2017, pp. 1–2.

[3] L. C. Hsiao, W. F. Huang, T. Y. Hsu, S. Y. Lin, H. L. Chen, and T. N. Wang, "Development of a Kinect-based bilateral rehabilitation game for children with cerebral palsy," Journal of the Neurological Sciences, vol. 381, pp. 191–192, Oct. 2017.

[4] G. Alankus, A. Lazar, M. May, and C. Kelleher, "Towards customizable games for stroke rehabilitation," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, New York, NY, USA, 2010, pp. 2113–2122.

[5] J. E. Deutsch, M. Borbely, J. Filler, K. Huhn, and P. Guarrera-Bowlby, "Use of a Low-Cost, Commercially Available Gaming Console (Wii) for Rehabilitation of an Adolescent With Cerebral Palsy," PHYS THER, vol. 88, no. 10, pp. 1196–1207, Oct. 2008.

[6] A. Fern'ndez-Baena, A. Susín, and X. Lligadas, "Biomechanical Validation of Upper-Body and Lower-Body Joint Movements of Kinect Motion Capture Data for Rehabilitation Treatments," in 2012 Fourth

International Conference on Intelligent Networking and Collaborative Systems, 2012, pp. 656–661.

[7] C.-J. Su, C.-Y. Chiang, and J.-Y. Huang, "Kinect-enabled home-based rehabilitation system using Dynamic Time Warping and fuzzy logic," Applied Soft Computing, vol. Complete, no. 22, pp. 652–666, 2014.

[8] D. Johnson and J. Wiles, "Effective affective user interface design in games," Ergonomics, vol. 46, no. 13–14, pp. 1332–1345, Oct. 2003.

[9] J. Sykes and S. Brown, "Affective Gaming: Measuring Emotion Through the Gamepad," in CHI '03 Extended Abstracts on Human Factors in Computing Systems, New York, NY, USA, 2003, pp. 732–733.

[10] O. Sourina and Y. Liu, "EEG-Enabled Affective Applications," in 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, 2013, pp. 707–708.

[11] C. Jennett et al., "Measuring and defining the experience of immersion in games," International Journal of Human-Computer Studies, vol. 66, no. 9, pp. 641–661, Sep. 2008.

[12] M. Csikszentmihalyi, Flow: the psychology of optimal experience. New York: Harper & Row, 1990.

[13] J. Chen, "Flow in games (and everything else)," Commun. ACM, vol. 50, no. 4, pp. 31–34, Apr. 2007.

[14] L. Nacke and C. A. Lindley, "Flow and Immersion in First-person Shooters: Measuring the Player's Gameplay Experience," in Proceedings of the 2008 Conference on Future Play: Research, Play, Share, New York, NY, USA, 2008, pp. 81–88.

[15] A. Drachen, L. E. Nacke, G. Yannakakis, and A. L. Pedersen, "Correlation Between Heart Rate, Electrodermal Activity and Player Experience in First-person Shooter Games," in Proceedings of the 5th ACM SIGGRAPH Symposium on Video Games, New York, NY, USA, 2010, pp. 49–54.

[16] C. T. Tan, D. Rosser, S. Bakkes, and Y. Pisan, "A Feasibility Study in Using Facial Expressions Analysis to Evaluate Player Experiences," in Proceedings of The 8th Australasian Conference on Interactive Entertainment: Playing the System, New York, NY, USA, 2012, p. 5:1–5:10.

[17] K. Gilleade, A. Dix, and J. Allanson, "Affective Videogames and Modes of Affective Gaming: Assist Me, Challenge Me, Emote Me," in DiGRA 2005: Changing Views – Worlds in Play., 2005.

[18] D. Johnson and J. Wiles, "Effective affective user interface design in games," Ergonomics, vol. 46, no. 13–14, pp. 1332–1345, Oct. 2003.

[19] G. N. Yannakakis, H. P. Martínez, and A. Jhala, "Towards affective camera control in games," User Model User-Adap Inter, vol. 20, no. 4, pp. 313–340, Oct. 2010.

[20] C. Liu, P. Agrawal, N. Sarkar, and S. Chen, "Dynamic Difficulty Adjustment in Computer Games Through Real-Time Anxiety-Based Affective Feedback," International Journal of Human–Computer Interaction, vol. 25, no. 6, pp. 506–529, Aug. 2009.

[21] G. Chanel, C. Rebetez, M. Bétrancourt, and T. Pun, "Boredom, Engagement and Anxiety As Indicators for Adaptation to Difficulty in Games," in Proceedings of the 12th International Conference on Entertainment and Media in the Ubiquitous Era, New York, NY, USA, 2008, pp. 13–17.

[22] D. Sharek and E. Wiebe, "Measuring Video Game Engagement Through the Cognitive and Affective Dimensions," Simulation & Gaming, vol. 45, no. 4–5, pp. 569–592, Aug. 2014.

[23] S. D. Craig, S. D'Mello, A. Witherspoon, and A. Graesser, "Emote aloud during learning with AutoTutor: Applying the Facial Action Coding System to cognitive–affective states during learning," Cognition and Emotion, vol. 22, no. 5, pp. 777–788, Aug. 2008.

[24] V. J. Shute, "Stealth assessment in computer-based games to support learning," Computer games and instruction, vol. 55, no. 2, pp. 503–524, 2011.

[25] R. Tadayon et al., "Interactive Motor Learning with the Autonomous Training Assistant: A Case Study," in International Conference on Human-Computer Interaction, 2015, pp. 495–506.

[26] Visage SDK. http://visagetechnologies.com/products-and-services/visagesdk/

[27] T. Baron, "An Architecture for Designing Content Agnostic Game Mechanics for Educational Burst Games," Ph.D. dissertation, CIDSE Softw. Eng. Poly, Arizona State Univ., Mesa, AZ, 2017.

[28] P. Ekman and W. Friesen, Facial Action Coding System. Consulting Psychologists Press, Stanford University, Palo Alto,1977.

[29] N. Bosch, Y. Chen, and S. D'Mello, "It's Written on Your Face: Detecting Affective States from Facial Expressions while Learning Computer Programming," in Intelligent Tutoring Systems, 2014, pp. 39–44.

[30] A. Koenig et al., "Real-Time Closed-Loop Control of Cognitive Load in Neurological Patients During Robot-Assisted Gait Training," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 19, no. 4, pp. 453–464, Aug. 2011.

[31] D. Novak, M. Mihelj, J. Ziherl, A. Olensek, and M. Munih, "Psychophysiological Measurements in a Biocooperative Feedback Loop for Upper Extremity Rehabilitation," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 19, no. 4, pp. 400–410, Aug. 2011.

[32] N. Shirzad and H. F. M. Van der Loos, "Evaluating the User Experience of Exercising Reaching Motions With a Robot That Predicts Desired Movement Difficulty," J Mot Behav, vol. 48, no. 1, pp. 31–46, 2016.

[33] R. V. Aranha, L. S. Silva, M. L. Chaim, and F. d L. d S. Nunes, "Using Affective Computing to Automatically Adapt Serious Games for Rehabilitation," in 2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS), 2017, pp. 55–60.

[34] J. Hamari, D. J. Shernoff, E. Rowe, B. Coller, J. Asbell-Clarke, and T. Edwards, "Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning," Computers in Human Behavior, vol. 54, no. Supplement C, pp. 170–179, Jan. 2016.

[35] M. S. Jungjin Kim PT and P. T. BumChul Yoon, "Patient perspectives on virtual reality-based rehabilitation after knee surgery: Importance of level of difficulty," Journal of rehabilitation research and development, vol. 53, no. 2, p. 239, 2016.

[36] K. d. O. Andrade, T. B. Pasqual, G. A. P. Caurin and M. K. Crocomo, "Dynamic difficulty adjustment with Evolutionary Algorithm in games for rehabilitation robotics," 2016 IEEE International Conference on Serious Games and Applications for Health (SeGAH), Orlando, FL, 2016, pp. 1-8.

[37] V. Shute, F. Ke, and L. Wang, "Assessment and Adaptation in Games," in Instructional Techniques to Facilitate Learning and Motivation of Serious Games, Springer, Cham, 2017, pp. 59–78.

[38] A. Drachen, C. Thurau, R. Sifa, and C. Bauckhage, "A Comparison of Methods for Player Clustering via Behavioral Telemetry," arXiv:1407.3950 [cs], Jul. 2014.

[39] R. Tadayon, T. McDaniel, and S. Panchanathan, "Autonomous training assistant: A System and framework for guided at-home motor learning," presented at the 18th International ACM SIGACCESS Conference on Computers and Accessibility, ASSETS 2016, 2016.

[40] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, "Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review," Psychonomic Bulletin & Review, vol. 20, no. 1, pp. 21–53, Nov. 2012.

[41] R. Tadayon *et al.*, "A Person-Centric Design Framework for At-Home Motor Learning in Serious Games," Arizona State University, 2017.