Work-in-Progress: Lessons Learned from Using Exergame, 3D Avatar-Based Feedback for Yoga-Self Training in a Preparatory Study

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ABSTRACT

As indoor self-training in sports has grown in popularity, yoga has become one of the most popular in-home exercise methods. However, yoga practitioners progress slowly or risk injury without qualified supervision. To address this issue, we propose a low-cost, camera-based exergame, 3D avatar-based feedback system for yoga self-practice. To assess our system, we performed a pilot study with eleven yoga students whose self-training was subsequently assessed by six professional yoga teachers. The results of this study hint that such an exergame-based approach has the potential to support yoga self-practice efficiently.

Index Terms: Human-centered computing—Visualization—Visualization design and evaluation methods

1 INTRODUCTION

During the COVID-19 lockdowns, exercise patterns were significantly impacted as people were forced to retreat to the confines of their homes, leading to increased sedentary behavior [4]. People were forced to reimagine their living spaces and recognize that maintaining physical well-being can extend beyond the confines of traditional gyms, as evidenced by the increasing trend of home-based exercise [4]. These situations of home confinement have negatively influenced the ability to receive appropriate medical care in case of injuries or conditions requiring continuous rehabilitation [18]. Therefore, providing safe and effective in-house exercise and training opportunities has become more critical.

Yoga, an ancient practice originating in India, has gained widespread popularity across the globe as a means to promote physical and mental well-being [12, 19, 21]. However, performing yoga postures beyond one's physical limits without guidance from a teacher leads to an increased risk of injury and muscular problems [5, 9, 14]. Also, trainees may progress slower without appropriate feedback and instruction [9]. Furthermore, as more individuals are embracing the trend of in-house exercising as part of their daily routine, many are practicing yoga without expert supervision [8, 10, 20]. In that context, yoga learning and self-instruction systems have the potential to help ensure safe and correct practice by enabling solo practitioners to self-correct their poses [25].

Augmented feedback, including those provided by technological tools like immersive [13, 18] and non-immersive 3D interfaces [16], can yield various advantages for enhancing the learning and execution of perceptual-motor skills in sports and other exercise regimes [23] such as augmented-reality-aided physical therapy [18].

In this context, we propose an exergame feedback system for autonomous yoga self-training supervision. Our system utilizes a low-cost laptop camera and relies on body pose estimation to provide individualized, real-time audio feedback on yoga poses with the help of a 3D avatar. Such applications can induce sports accessibility, allowing people to benefit from exercise despite the lack of proximity to gyms or fitness classes. As a result, it may help to reduce the likelihood of injuries and amplify participants' performance [25].

To that end, we conducted a pilot user study with yoga students and teachers to ascertain the usability of exergame feedback and explore the potential challenges in yoga automated instruction.

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2 EXERGAME SYSTEM DESIGN

When designing a yoga self-training system, we must first consider several factors, such as structuring the yoga practice and feedback in the most accessible manner. Thus, we decided to rely on a low-cost laptop-based setup and a mixture of visual and audio feedback. The system consists of the following four parts.

1. Human Pose Estimation: To generate virtual human representation in real-time, we used well-known open-source packages, i.e., MediaPipe [15], OpenCV [6], and MoveNet [1]. Thanks to them, we were able to prototype a robust real-time virtual human representation and motion analysis.

2. Yoga Pose Classification: We built our classifier using a convolutional neural network (CNN) [26] architecture for pose prediction. The CNN was trained on the Yoga-82 dataset from [24], which offered a well-labelled (in Sanskrit and English) rich hierarchical structure (including body positions variation) that we could leverage to improve pose estimation performance.

3. Real-Time Pose Correction: The classification model checks the alignment of five major yoga pose components, including the angles between the head and neck, as well as the right and left sides of the shoulder, arm, hip and knee. The challenging part of pose correction is determining a threshold of how large a difference the user should be from the target pose. Presently, there are a plethora of options for defining a correct pose [3]. Here, we decided to use the angle differences as suggested in prior research [3, 22]. The angles of the student's pose are compared to the angles of an image of a target pose in real-time. Any detected deviation of more than 15° from the target pose will result in the student receiving audio-based feedback for correction. We used this particular threshold based on previous research suggesting a range of 10° to 20° for yoga experts and beginners respectively [3].

4. Avatar-Based Visual Feedback: The camera-based input from the hip and joint rotations was visualized back to the yoga students using a 3D avatar (Fig. 1(a)).

3 PILOT USER STUDY

3.1 Part I: Self-Training with Yoga Students

The study was conducted with eleven participants between 21 and 32 years of age, hereinafter referred to as P1-P11. Six of them were female (P1, P3, P4, P8, P9, P10), and five were male (P2, P5, P6, P7, P11). They represented diverse levels of yoga, anatomy, and exercise backgrounds, as well as different levels of flexibility and strength.

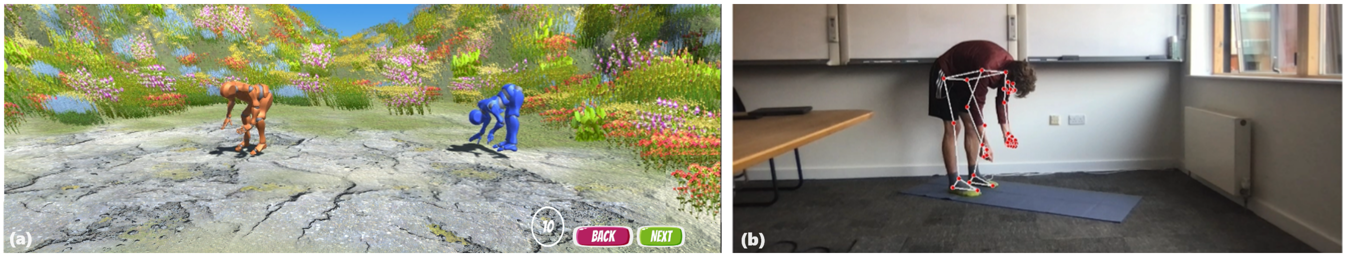

Figure 1: Side-by-side view of the pilot study showing P6 as his (a) 3D avatar and in (b) camera feed.

They were all prescreened for medical conditions that would prevent them from safely parking in our study.

When the experiment started, the participant was placed on a yoga mat in front of a laptop and an external monitor to perform a predefined, 20-minute-long yoga sequence, as shown by the 3D avatar (see Fig. 1). Each participant had to work through each from a six-set pose set: (1) *Standing forward bend*, (2) *Chair* (3) *Plank* (4) *Upward facing dog* (5) *Downward dog*, and (6) *Warrior 1*. The sequencing of poses belonged to *Sun Salutation A* (1) → (3) → (4) → (5) subsequently followed with *Sun Salutation B* (1) → (2) → (3) → (4) → (5) → (6).

The next pose was automatically loaded once the participant executed a given pose, i.e., holding it for 10 seconds. These poses were then automatically assessed and corrected with audio feedback when needed. To allow visual comparison, the current participant's pose was visualized as an orange avatar next to the blue demonstrator (see Fig. 1(a)). Another window on the screen also showed the student's pose using their physical self (see Fig. 1(b)).

As the student moved through the yoga sequence, we captured audio and video, including the screen with avatars and participants' physical selves. To complete the experiment, participants were asked to complete the NASA Task Load Index (NASA-TLX) [11] and System Usability Scale (SUS) [7] questionnaires. Finally, we conducted an interview asking for general feedback and requested that participants subjectively assess the alignment of their poses as their physical and avatar selves.

3.2 Part II: Self-Training Evaluation with Yoga Experts

Nine yoga experts participated in our study, hereinafter referred to as E1-E9. They all hold professional yoga training certificates and/or relevant years of practice. Before designing the system, a survey was sent to three yoga teachers (E1-E3) for feedback regarding our instructions and transitions between poses. The feedback from the experts was implemented within the avatar's limits.

The remaining six yoga teachers (E4-E9) assessed the feedback provided by the avatar and the students' alignment based on recorded data. The latter included students' pictures and corresponding avatar visualization (see Fig. 1). The expert evaluation results were subsequently compared to the students' self-evaluation and automatically calculated system scores. The score of the teachers' evaluation was based on a litmus scale that was then averaged by the five-body alignment. The scale rated the student's alignments comprising poor (1%), unsatisfactory (25%), satisfactory (50%), very satisfactory (75%) and outstanding (100%). In addition, the experts evaluated the automated system feedback in a similar manner.

4 Study Results

4.1 Questionnaires‘ Results

In terms of NASA-TLX sub-scales, participants provided the highest scores for the mental demand, followed by temporal demand and then effort, which, in other words, suggests that the task is mentally demanding, hurried and requires a high level of effort. The highest recorded NASA-TLX weighted score was given by P7 (89.7) and P1 (85.0), with the lowest given by P3 (30.0) and P6 (30.0). The remaining participants scored between 50 and 70.

In interpreting the SUS results, the experience of using the system can be described as marginally acceptable [2] by seven participants, with two participants, namely, P6 and P8, giving scores of 72.5 and 85.0, respectively. However, we strongly advise caution when assessing these results due to the experiment's small sample size and preliminary nature.

4.2 User Remarks and Comments

In the post-questionnaire, we asked about the participants' experience and to rate the system components (i.e., user interface, individualized feedback, audio instructions).

Eight students answered in the post questionnaire that they are somewhat likely (P3, P2, P4, P6, P8, and P10) to use the system, with two (P5 and P11) saying that they are very likely to use it in the future. Seven participants (P2, P4, P5, P8, P9, P10 and P11) stated that the system offers a low entry barrier to personalized yoga without the time constraint and availability of in-person or online yoga classes. In the survey, P2 also remarked that she *preferred the system over* [online] *videos, as pose correction, is available*. Moreover, P8 stated that he *doesn't feel comfortable in one-to-one online classes* [...] *but this system has the advantage of personalized evaluation and feedback*. Whereas P10 stated that she would like to try yoga, she *would use the application because it is cheaper than joining a yoga class* [as] *the app also gives you feedback, and you can do it at home*. Furthermore, out of six participants who reported previously tried yoga classes via video conferencing tools, five preferred our system over these alternatives.

The rest of the study participants stated that they are neither likely nor unlikely (P9) and very unlikely (P1, P7) to use the system. Their main concern was that the student avatar had a noticeable time delay in mirroring the movements, and often, the teacher avatar moved slower than the student. P9 also mentioned that the feedback was somewhat overwhelming as the system did not help teach a yoga pose, and she deferred to her yoga knowledge. She also reported one of the highest TLX scores of 70.7 and a low SUS score of 45.0.

At the same time, she (P9) and a few other participants (P2, P4, P8) mentioned that they would be more inclined to use and pay for such an application once the observed issues are resolved. According to some comments (P2, P6, and P8), the system needs to be extended with more nuanced yoga knowledge. For example, P8 reflected that he *would first watch some tutorials on basic yoga poses to be able to understand the instructions that the avatar teacher gave*, while P6 had problems understanding some yoga terms, making the instructions difficult to follow. Moreover, P7 and P8 found the speed of the audio delivery too fast.

In terms of the avatar, P3, P6, and P10 preferred to see themselves instead of the avatar (see Fig. 1), P5 and P8 preferred seeing both their physical and avatar self. On the other hand, P4 and P9 did not have a preference. Here, P6 and P8 reasoned that the avatar allowed easier comparison to the teacher avatar. In contrast, P2 and

P8 commented that correcting the pose as their physical self was easier.

In addition, P3, P8, and P10 discussed feelings of self-consciousness in comparing their preferences for the physical or avatar self. P8 remarked that when participants are self-conscious, focusing on doing the pose correctly would be problematic if they kept looking at their physical selves. P10 said she preferred what the proposed system did, which was to show a neutral avatar. Furthermore, P7 said that he was more critical in reviewing his body alignment when he saw his physical self. Further, he commented that *for people with body confidence issues or body dysmorphia, there is potential for introducing the avatar as a "comfort zone"*.

4.3 Subjective Usefulness of System Feedback for Yoga

We also asked the participants how useful and understandable different system components were for executing the poses correctly. Based on this feedback, we created a correlation matrix to examine dependencies between the student ratings and SUS scores. In analyzing the positive correlations with a score of over 0.7, the higher the SUS score, and the higher the understandability and usefulness of the visual of the teacher avatar in correcting the pose, the higher the preference for the avatar self. When looking at positive correlations with other variables, the SUS score had a positive correlation between 0.6 and 0.7 with the understandability of the individualized feedback, teacher avatar, student avatar, and the usefulness of the teacher and student avatar.

Furthermore, students with regular sports habits (P2, P4, and P9) found the audio instructions more useful and understandable. As expected, the usefulness of the audio instruction correlated positively with the understandability of the individualized audio feedback.

With regards to avatars, students (P5, P6, P8, P10, and P11) who found the student and teacher avatars useful also found the avatars understandable. As expected due to their similarity (see Fig. 1(a)), the understandability and usefulness of the teacher and student avatar were strongly correlated.

4.4 Posture Alignment and Feedback Ratings

We asked participants and yoga teachers to rate the alignment of their poses against the avatar-self for eight students. The average scores revealed that participants consistently rated themselves higher than the system average. In contrast, the teacher and system were more in sync concerning student evaluation, considering that the difference was only between 4% to 13%.

We also observed a difference between the system and teacher evaluation in the first two participants (P1, P2), which can be attributed to researchers not providing adequate explanations before the experimental phase and the mispositioning of the first two students in the camera's field of view.

The yoga experts (E4-E9) were asked to rate the quality of feedback, resulting in an average score of 79%, with feedback ranging from 66% to 91%. The score of the teachers' evaluation was based on a litmus scale that was then averaged by the amount of feedback. The scale rated the suitability of the feedback from extremely unsuitable (1%), somewhat suitable (25%), satisfactory (50%), very suitable (75%) and extremely suitable (100%).

4.5 Yoga Exercise Observations

Students Positioning: Our tests suggest that the students' poses were better recognized when facing 45° towards the camera. However, it was difficult for the users to view the on-screen avatars in such a pose. Secondly, their whole body needed to be detected. The students also had to break their exercise to move to the next pose by pressing the $[NEXT]$ button (see Fig. 1)(a)). Here, using a simple voice command could be a potential solution.

Lighting Conditions and Clothing: As expected, poor lighting conditions could affect body posture tracking. Similar effects were caused by the dark clothing colours that had low contrast with the background.

Participants Behavior: When the pose constrained the avatar view, participants ignored the system and used their previous yoga knowledge or audio instruction.

4.6 Yoga Experts Evaluation

We conducted audio and video-recorded online call sessions with the invited yoga experts (E4-E9), who answered the same post-experimental survey as the yoga students.

All yoga teachers prefer to correct the participants' physical selves rather than their avatars. They reported a clearer understanding of how students bent or engaged their muscles or limbs. For example, it was more visible to see where the students were gazing or what they were doing with their fingers and feet. A yoga teacher in a studio has a view of all sides of the students to understand what body parts could be aligned, while the system provides only the front view. E3 and E5 stated in the interview that evaluating the student's pose is difficult because it is just a static image of one view. At the same time, she (E5) would need to have a grasp of viewing the other side of the student to understand better if the pose was done correctly.

In addition, the fingers and toes of the avatar need more detailed tracking and visualization. For example, it was hard to tell if the fingers were spread and pressing against the floor or if the heels were touching the floor. As the avatar's position was based on a skeleton figure, E2 said it is challenging to notice a rounded back or slouch to indicate poor posture. This feedback was mentioned by a few yoga teachers as they were seeing a seemingly straight back, even though the person was slouching or rounding their back as the teachers were assessing students' avatar self.

Recognizing if the student's knee was straightened was not accessible from the avatar's look, which was especially important in the poses where teachers needed to understand a person's flexibility. Some training cues directed students to gaze in a particular direction, but it was not easy to see where the student was looking, as noticed by several yoga teachers.

Yoga teachers remarked that during in-person classes, they have a better feeling of what muscles the students are engaging and rotating or if joints are tense. In some poses, students need to rotate their shoulders, which is not clearly deductible from a single perspective. In other cases, students may compromise their pose as they get tired and no longer engage their core muscles. Such an issue may be detected more easily in an in-person class when one can see how loose the core muscles are. From a single perspective of a student, it would be possible to detect a lack of core engagement based on small nuances such as the student's hip dropping and the shoulders slouching, as mentioned by E5, but the poor alignment is not easy to diagnose from the same data.

5 Lessons Learned

Based on the study carried out with yoga students and experts, we outlined several tentative design suggestions that we will use to refine our system design and implementation.

1. **Yoga Sequence Difficulty Customization**: The system should be adjusted to the practitioner's yoga advancement level and experience by adapting the aligned threshold in a given range of 10° to 20° for yoga beginners and experts, respectively [3].

2. **Synchronization of Visual and Audio Feedback**: As we used low-cost equipment, we observed occasional audio and visual feedback misalignment. As a result, students were at times not sure if they should follow the audio instruction or visual guidance from the avatar. P2, P7, and P9 commented on the

occasional avatar's delay negatively affecting synchronization as the audio moved faster than the avatar's visual movements.

3. **3D Pose and Joint's Rendering**: The system should render a realistic depiction of the finger and toe movements as commented by all the yoga experts. E4 remarked that it was unclear from a single perspective if the student was pressing the ground away with the fingers, which is essential for some of the poses.

4. **Additional Visual Feedback**: As the students received audio feedback, they were sometimes unaware of which part of their body the audio feedback referred to. Hence, additional visual guidance could be provided to the student to draw attention to posture mistakes by highlighting the particular body area as performed in [22]. Earlier work marked the joints on a user's visual representation as a stick figure with colour gradients that highlighted the extent of the error of the joint and forced self-learners to correct their pose [22]. A similar approach was also suggested by yoga student P5 and expert E5.

5. **Avatar Options**: It could be valuable to allow students to view themselves on a screen or as an avatar (see Fig. 1). Another approach would be to have a gender-based avatar, as suggested by E2, given the differences in anatomies between the genders.

6. **Student Positioning**: The student and the screen should be positioned for a comfortable view. In our study, the participants had to face the screen from a 45°angle for better body tracking, which was often uncomfortable as they had to tilt their heads to view the monitor, as reflected by the students (P3, P9, P11).

6 Conclusion

In recent years, exercise patterns and habits have been significantly impacted. Because of this, we could observe a growing trend of home-based exercise [4]. In turn, these changing habits have incentivized the development of new solutions to guide a person to perform yoga or other exercises independently without needing an instructor and in the comfort of a practitioner's home.

To that end, this paper shows a work-in-progress system for personalized feedback from the virtual yoga coach. Based on the preliminary user study with eleven students, we have drawn a range of lessons related to the design of such avatar-based systems for user self-training. Despite the low SUS scores, the results show a promise that computer-supervised self-training has the potential to assess users' body alignment like that of an actual yoga instructor. In the future, we plan to improve usability by making the visualization of human movements more realistic to consider the tilting of the head, tracking and showing the gaze direction, as well as providing higher accuracy of the fingers and toes. Our initial findings will help guide future exergame designs for both immersive [13, 18] and non-immersive settings [16] utilizing 3D avatars [17].

Moreover, when designing such systems, we must consider that everyone's anatomies and body flexibility differ. Hence, it is hard for a system to define the "correct" pose. Physical limitations may also come from a previous injury or anatomical limitations. These situations can be mitigated by in-person yoga classes. On the other hand, we could argue that the yoga teacher could provide little attention to individual students in large classes. At the same time, the automatic detection of such feats remains a highly non-trivial task. Nonetheless, as proven in earlier work [18], exergame systems have the potential to help disabled learners or people undergoing in-home rehabilitation. In addition, such approaches can help those who, for various reasons, are unable to or do not want to attend an in-person class.

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