VR Alpine Ski Training Augmentation using Visual Cues of Leading Skier

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Abstract

Alpine skiing has strong environmental dependencies and the way of teaching the movement is believed to be incremental and cyclical. Training alpine skiing on simulators is a challenging work, especially when supporting experienced learner to improve to higher level. In this paper, we propose several vision augmentations for learning from a recorded expert skier motion in the way to replay the motion as a virtual leading skier.

The system uses an stationary indoor ski simulator and a VR System for prototyping, two VR trackers are used to capture the motion of skis so that users can control the skis on the virtual slope. For training, we captured the motion of professional athletes and replay it to let the users follow the experts in the slope. To support users, 6 different visual cues are introduced from different perspectives of learning skiing, such as the feet angle or the lateral position.

To explore the utility of visual cues and to study how users could learn the motion patterns from the expert-skier effectively, we performed qualitative and quantitative evaluations. In addition, we also studied several visual feedback aiming to help the learning process. The work provides the basis for developing and understanding the possibilities and limitations of VR ski ski training, which also has the potential to be extended to AR/MR use in real world.

1. Introduction

As one of the most famous winter sports, alpine skiing attract populations who is enthusiastic to practice it every year. Training of skiing is always restricted to the ”3S” requirements: season, skis, and slope. Therefore, plenty of facilities, including large scale slope simulators and indoor ski simulators, are developed to solve this problem. However, despite of the environmental dependencies, another difficulty is the method of training. Different from other sports, in which a learner can view and follow an expert's motion directly during the sports, it is not possible for a beginner to follow an experienced skier on the slope. Meanwhile, it is also difficult to copy the motion from recorded video without actively practicing it or to notice the difference between the expert and own motion. Typically, an instructor has to tell the learner directly how to correct the forms, which makes the adaptions cycles of learning skiing indirect and slow.

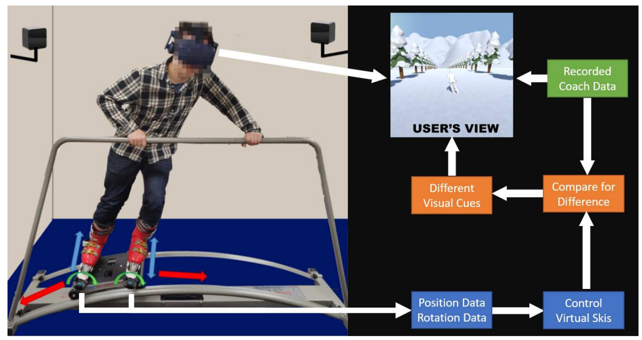

Figure 1. System Overview: The motions of user and expert are used to provide visual cues for ski training.

Ski training on simulators has been studied for years and there are already some solutions very close to real skis. Unlike other works [2, 24, 22, 14, 1, 21] which study the simulator itself (such as how to make the experience more realistic), we want to focus on the visual feedback provided to the user to improve their skills. Previous research of Nozawa et al. [15, 16] already shows the potential of using captured motion of an expert and visualizing it as a leading skier to teach alpine skiing in VR, but they include few quantitative result of the training effect.

Therefore, in this paper, we introduce 6 types of visual augmentation to enhance a virtual ski training and study its effect. Two experiments were performed to evaluate different visualizations from the perspective of training effect and user acceptance. Similar to other works studying virtual skiing [27], a VR head mounted display (HMD) was used create an immerse ski environment because its naturalness for skiing since athletes usually wear a goggle. As shown in Figure 1, the motions of a recorded expert skier are shown on a virtual slope to lead the user. Two tracking devices capture the rotation and position of user's feet to control the virtual skis. The difference between user and expert is then calculated and used for providing different visual cues to support the user to correct their form.

To conclude, the goal of this work is to provide visual augmentation to support the users to learn from an expert motion. As an essential first step, we developed 6 types of VR visual aids focusing on different part of the motion to support this process. We compared the performance of various visualizations in 2 experiments to better understand their benefits and drawbacks. Our studies provide insights in how to design a training support visualization which are not limited to VR or simulator usage, but also has the potential to be applied to real skiing using AR/MR technologies.

2. Related Work

This research builds on a number of works that contributed to the domain of alpine skiing, which can be mainly divided into three parts: Studies of training for alpine skiing; Augmentations on skiing; and Visualization methods for other sports.

2.1. Alpine Ski Training Study

The first skiing simulator for exercise was patented by Neuberg and Meserol [13] and simulates the skiing motion mechanically. Nourrit et al. [14] conducted an early study on skiing skill acquisition on a ski simulator. They examined the qualitative behavioral reorganizations when training on a ski simulator, and their studies show that it is possible to acquire complex motor skills that way. However, they do not consider the efficiency or speed of the learning. Panizzolo et al. [17] studied the efficacy of ski simulators, which are representative for the two most common simulator types. Two ski simulators, a slope simulator that uses a rolling carpet (Skimagic®[1]) and a motion simulator, which allows for lateral movement (Skier's Edge®[2]) were compared to skiing on natural snow. They used EMG signals and kinematic data to analyze muscle activation pattern during skiing. A good correlation of activation patterns corresponded to a better simulation of the skiing movement. The result shows that both simulators do have similar pattern to real skiing, and the slope simulator (with more degrees of freedom) performs 17.1% better in muscle training. '

2.2. Augmenting Alpine Skiing

There are a number of works that augment alpine skiers with sensors. Some of these systems are purely designed to collect data, which is analyzed and reviewed later. Brodie et al. [4], for instance, combined several sensor inputs (e.g. IMU, GPS) for capturing and analysis ski motions. The data is considered to be viewed by coaches to analyze the movement patters of their athletes in order to increase performance and reduce injury potential. VR is deployed by Kobeissi et al. [10], who augmented a balance board with a motion sensor. Their method can help users to improve their control of balance, but the feeling of standing on a balance board is far from real skiing.

More recent works aim to process the collected data right away and provide the feedback directly to the skier on the slope. One way to do so is audio feedback with is used by Hasegawa et al. [7], who developed a device to provide real-time sonification of the center of gravity of the skier, which can guide the skier and overcome the reaction of leaning back. Fan et al. [6] augmented skiers using an AR HMD. Their work was demonstrated on a 20-meter gentle slope where AR objects were visualized to the user. The work shows the possibility of using an HMD to replace goggles to provide visual information. This idea was picked in commercial products, such as the Recon Snow2[3] or the RideOn Ski Googles[4]. The first one also being used by Kos et al. [11]. Using bend and force sensors, which are applied to both skis to measure the deformation during skiing, their system also featured real-time biofeedback, presented in a head-up-display within the ski googles.

However, above-mentioned technologies are developed to be used in combination with real skiing and require a real slope environment.

2.3. Other Sports Visulization

Research shows that Virtual Reality (VR) technologies can be useful in sports training [3]. Consequently, VR-based training methods have been applied to various sports. Mikami and Takahashi et al. [12, 23] created a VR-based baseball training system and tested it on a professional baseball team. In their work they analyze the motion and heart rate of pro and amateur athletes to understand the underlying cognitive processes that occur during the game. Another application is golf training as proposed by Ikeda et al. [9, 8]. A mixed-reality system is used to replay the recorded motion of an expert golf player. The user can view the motion slowly and gradually to gain feedback on the difference between the own and the coach's swing. However, this is difficult to do in continuous high speed sports such as skiing. Dance is another skill that requires a lot of body awareness and also an elaborated understanding of the target movement. This is why dancing is often practiced in a room full of mirrors. Chan et al. [5] used VR and a motion capture system for observing one's own performance. Users can view playbacks or change the view point to get better understanding of their movements. In martial arts, VR-based training methods are also widely used. Chua et al. [18] presented a VR system for training Taichi, which enables to adjust the time scale in the virtual environment. This enables users to follow the movements of professional teachers and

[1] http://www.skimagic.it/eng/skimagic-indoor/index.html
[2] https://www.skiersedge.com/products
[3] https://www.intel.com/content/dam/support/us/en/documents/emerging-technologies/wearable-devices/Snow2_User_Manual_May_2016.pdf
[4] https://www.rideonvision.com/new/

Figure 2. Data capturing of a professional skier on a ski simulator using an eight-camera OptiTrack system.

match their speed. Wu et al. [25, 26] introduced a mixed reality training system for boxing, in which a deep learning method is used to forecast the pose of the instructor and visualize the future 3D pose in VR. All these examples show that VR can be a useful technology for skill acquisition in sports, strengthening our believe that it also provides a benefit in the domain of alpine skiing.

3. Methodology

This work aims to enable a vision-based skill transfer between professional skiers and learners. Besides the difficulty of approaching world class athletes for a training session, copying their movements in a dynamic sport such as skiing is an additional challenge due to the complexity of the motion and the general speed on the slope. Therefore, we wanted to create a system that can visualize the motion patterns of professional skiers to normal users. The overall idea is to capture the movement data of the expert and replay it to the learner to provide them with different type of visual cues of the expert's motion. To remove the complexity of a real terrain and the progress, we use a simple stationary ski simulator. Note that the visualizing method itself is not limited to specific simulator and might be even reproducible on real slope.

3.1. Data

Hereby, expert's data are required as a "Ground Truth" of optimal motion. To capture expert data for our system we invited two athletes, who were former alpine ski world cup racers. They were asked to perform rhythmic slalom turns on a professional ski simulator (SkyTechSport Alpine Simulator[5]). This advanced simulator provides 3-DOF and uses an electric motor for moving the skis. We captured their real-time full body motion using an OptiTrack Motion Capture System with eight cameras (Prime 13W[6]) as shown in Figure 2.

3.2. System Design

Our training system consists of an indoor ski simulator, a VR system (HTC Vive Pro[7]), and a pair of tracking sensors. Since real skiing also requires a helmet and goggles, which narrow the field of view, the use of a HMD does not greatly disturb the skiing experience. We used a Pro Ski®-Simulator Power Ski Simulator[8]), which simulates the skiing motion similar to the Skier's Edge simulator mentioned in related work. The user wears ski boots and steps into the ski bindings mounted to the stand, which can rotate and move in 3-DOF (see Figure 1) similar to the SkyTech Sport Alpine Simulator only with a smaller horizontal range. As also shown in Figure 3, we mounted the two VR trackers on the skis to capture their position and rotation. Since we used a simple stationary ski simulator, the skis are not able to rotate around the up axis, which means the users cannot do motion such as turning. However, the skies can be moved sideways to simulate turns. When moving away from the center a counterforce is created by the rubber bands of the simulator which pull the skis back into the center position. The strength of this force can be adjusted by changing the number of the rubber bands used.

For the training in VR, we created a virtual ski slope environments in Unity 3D. As its main purpose is to serve as a test environment for different visualization, we designed a plain, smooth, down hill ski slope with a steadily increasing grade. We used a predefined splines to simulate the user's movement along a designed course. Since the users can move sideways on the simulator to a certain extend, they are able to mimic the lateral movement and the feet motion of a leading expert skier.

3.3. Visualization Methods

In order to obtain more general idea of VR skiing, a previous pilot study was performed in an international VR conference as a prototype demonstration [15]. In total, 82 participants took part in the pilot study and experienced the first 3 visualizations introduced in this section. An overall questionnaire to rank each condition was performed to the users, together with an optional interview which mainly targeting participants with skiing experience. The visualization methods in this paper are developed on the basis of the result of the study.

After all, We developed and implemented 6 interface variations with different visual cues to enhance the skiing, together with 1 baseline visualization for comparison, as shown in the Figure 3:

[5] http://www.skytechsport.com/alpine-simulator

[6] https://optitrack.com/systems/#virtual-reality/prime-13w

[7] https://www.vive.com/eu/product/vive-pro/

[8] https://www.ski-simulator.com/power-ski-simulator-en

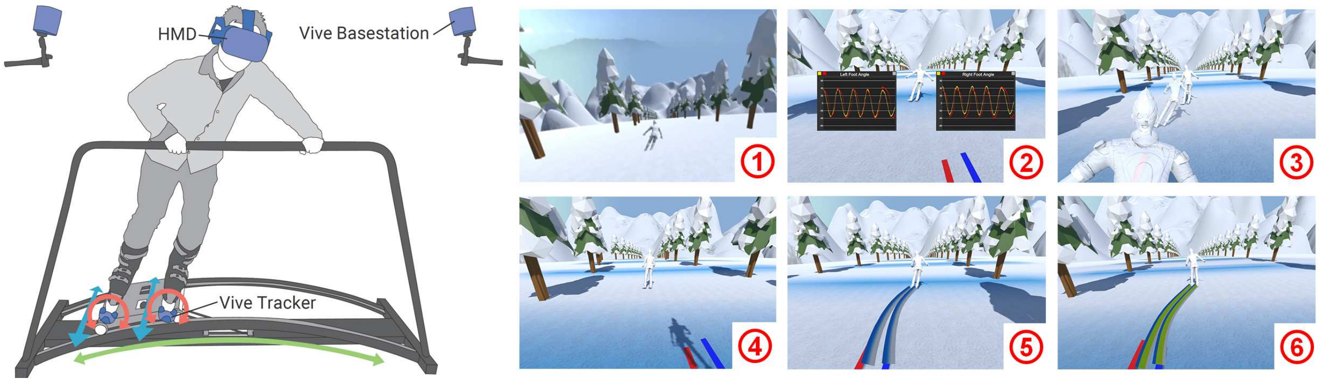

Figure 3. System Design: The left part is the hardware system, the right part shows the 6 visualizations introduced in this paper.

Follow the Trajectory (Baseline): This is the baseline condition where no extra visualization is provided (same as ① in Figure 3), which is quite similar to real skiing. Users have to follow the trajectory of the recorded leading expert who starts 1 second in advance, i.e. carrying the motion out when being on the same point of the slope. In this condition, the coach is acting a kind of "future optimal" while the users have to observe and remember the motion to move after it, which is proved to be difficult in past studies [27].

① Mimic the Motion: This is a simple tweak of the baseline condition, the visual cues are the same (① of Figure 3). However, in this condition, the leading skier is not the "future optimal", but the "current optimal" by simply delaying the expert's motion according to user's position, which means the user only need to simply observe the motion and perform at the same time instead of following their path. This will provide the real-time ground truth to user which is very difficult to realize in real world.

② Angle Graph: The *Angle Graph* condition enables the users to compare their angle value of each foot to the expert in a separate graph (② of Figure 3). In each graph, there is an yellow line to show the expert's angle and an red line rendering user's angle. Since the base condition of the graph is *Follow the Trajectory*, we delayed the data of the expert presented in the graphs to meet the user, which means the user should try to overlay his line on the expert's. The position of the graph is fixed on top of the slope but not fixed to user's view. That's because previous study of Nozawa et al. [16] claims that fixing something to user's view will attract user's concentration from the coach and disturb their performances.

③ Pose Breakdown: To better visualize both the temporal and spatial information of the expert's motion, another visual cues that shows the sequential poses of the professional is developed (③ of Figure 3). This is done by rendering static copies of the expert avatar in even intervals so that the users can match the motion and position. This function is designed to provide extra visual cues to support users with following the expert's trajectory correctly.

④ Expert Shadow: Another idea is to place the shadows of the expert's avatar rendered in the *Pose Breakdown* on the ground, while the body is made fully transparent and this way invisible. From this initial idea we finally use a single shadow that continuously shows the target position of the user (see ④ of Figure 3). Using shadows for learning movements from experts has already been explored successfully in other sports, such as golf [9]. The aim of this method is to provide a more natural and less invasive visualization of expert's temporal motion.

⑤ Trail: In the pilot study, there were some reaction to the controversial statements that described the *Pose Breakdown* as too invasive, we introduced a trail visualization as a more lightweight alternative. The trails, which consist in pairs, one for each foot, do not only show lateral movement but also rotation by being rendered as a 3D ribbon to indicate the ankle rotation of the expert. As this rotation was initially difficult to see we added a gradient texture and cut the trails off right at the users skies so that the area of intersection reveals the rotation as shown in ⑤ of Figure 3.

⑥ Colored Trail: During the pilot study, whether to render more feedback on the trail became an argue point. The graphs were considered quite overwhelming by some participants, hence, we searched for simpler ways to provide feedback. Our observation was that it is hard to adapt to a single value that is constantly changing and that the feedback should rather help to quickly judge the current performance. Thus, we looked at ways to summarize the user's performance so that it can be perceived in one glimpse. This led to the use of color as a performance indicator (green = good, red = bad). After experimenting with various individual UI elements we integrated this colored trail approach (⑥ of Figure 3) to minimize the need for splitting attention between different UI elements.

4. Experiment

In our experiments, we conducted both quantitative evaluation to study the usability of the system, and qualitative evaluation to study the effect on improving skiing.

4.1. Participants

For both experiments, we invited 14 participants (6 female) with an average age of 25.5 (SD = 6.9) including students and administration staff from computer science department at the local university. Within the participants, five have hardly any skiing experience, five is intermediate level, while other four can be considered more experienced.

4.2. Procedure

After an initial briefing in which we introduced the different conditions and the goal of the study, the participants were asked to put on ski boots and step on the simulator. They could familiarize themselves with the movement on the simulator before they put on the HMD. We then started the simulation which presented the different conditions to them. The order was randomized using Latin square. Each condition consisted of 1 training trial to get familiar with the visualization and 2 test trials. Each trial started with an 8 s countdown, to pick up the movement pattern and was then followed by a 30 s trial period. After each condition, the participants were asked to qualitatively rate their experience in a question sheet. After performing all 7 conditions the semi-structured interview was conducted. The entire process took approximately 45 min. per participant (10 min. briefing, 20 min. study, 15 min. interview).

4.3. Quantitative Evaluation

Since it is difficult to quantify the level of skiing directly, we focused on two specific values: ankle rotation (AR) and lateral movement (LM). Even though comparing movement pattern quantitatively is considered to be not trivial in most sports, however, in this specific experiments where the user's movements is mostly restricted by the ski simulator, focusing on a small number of metrics could reflect the level of the athletes. The ankle rotation was processed individually for each foot, the lateral movement subsumed was into a single value, as the ski simulator we used does not allow for individual lateral movement. Ankle rotation and lateral movement are represented in a time series, which were normalized to provide a value for each 10 ms. In addition, the lateral movement values were centered by deducting the mean of the time series from each value x_i ($x_i^{'} = x_i - \bar{x}$). As the goal of this experiment was to find a visualization that helps to mimic the motion of a professional we compare the motions using an error metric, where a perfect match of the movements would be considered an error of 0. A common metric to compare two signals is Dynamic Time Warping (DTW) [19] which was mainly developed to match audio signals [20] but was also already used for motion comparison of golf swings [9, 8] in an adapted version. However, as the DTW is specifically designed for dealing with temporal drift it would skew our result as the correct timing is an important factor. Hence, we use the area between the curves in a normalized form as a metric, which can be expressed in the following expression:

$$err = \frac{\sum_{i=0}^{n} |e_i - u_i|}{n}, \tag{1}$$

where err is the calculated error, whereas e_i it the expert's ankle rotation / lateral movement at the time i and u_i the user's rotation / movement at i. In the case of the ankle rotation the error is calculated for both feet separately and averaged at the end. This metric also provides us with meaningful error values which in the case of ankle rotation represents the offset between the target value in degree and in the case of lateral movement in meters. Note, that while for the experiment users were asked to pay attention to their ankle rotation as well as the movement, the conditions that provided feedback (*Graph*, *Trail with Feedback*) only provided feedback on the ankle rotation, as we considered this metric that is harder to perceive and adapt to.

4.4. Qualitative Evaluation

Besides the quantitative metrics we also captured qualitative data, because the creation of the different visualizations was an iterative process. The initial idea was to provide a way to improve skiing at a high level by imitating a professional skier. When designing these visualizations, we are facing the balance between the quantity of information and the usability. The optimal situation should be that users can handle all the feedback while not losing their focus on the coach motion. In this qualitative evaluation we aim to validate the assumptions that drove our development and try to get a better understanding the benefits and drawbacks of the different visualization methods. We asked the user five questions (Q1 Q5 as shown in Figure 5) and let them answer using a 6-point Likert-Scale. With these 5 questions, we aim to find out:

- What is the effect of mimicking the motion with no latency comparing to follow the trajectory.
- What visual cues makes the users feels that they improves the performance most.
- What visual cues is the easiest for user to understand.
- What is the effect of feedback on the performance.

In addition, we conducted a semi-structured interview to gather more in-depth feedback.

4.5. Result

When conducting the study we noticed that participants repeatedly used the 8 s countdown between the trials as a phase to rest and started with the movement only when the countdown had passed. To avoid compromising our result by the resulting noise we only used the data from second 10 - 30 per trial for the analysis.

For the quantitative experiment result (as shown in Figure 4), after processing the raw data as described in the performance metrics section we conducted a repeated-measures ANOVA ($\alpha = .05$) on the ankle rotation as well as lateral movement data. For both datasets a significant difference between the conditions could be detected (ARot: $F_{6,162} = 15.837, p < 0.001$; LMov: $F_{4.23,114.16} = 19.896$, $p < 0.001$). As for the lateral movement the assumption of sphericity was violated the Greenhouse-Geisser corrected values are reported. Tukey's range tests as post-hoc unveiled several significant differences between conditions.

The five Likert-Scale questions that were asked for each condition were analyzed by the Friedman tests, which were significant for all questions (Q1: $\chi(6) = 22.35$, $p < .005$, Q2: $\chi(6) = 18.84$, $p < .005$, Q3: $\chi(6) = 24.53$, $p < .001$, Q4: $\chi(6) = 18.90$, $p < .005$, Q5: $\chi(6) = 14.9$, $p < .05$) and pairwise Wilcoxon Signed Rank tests as post-hoc.

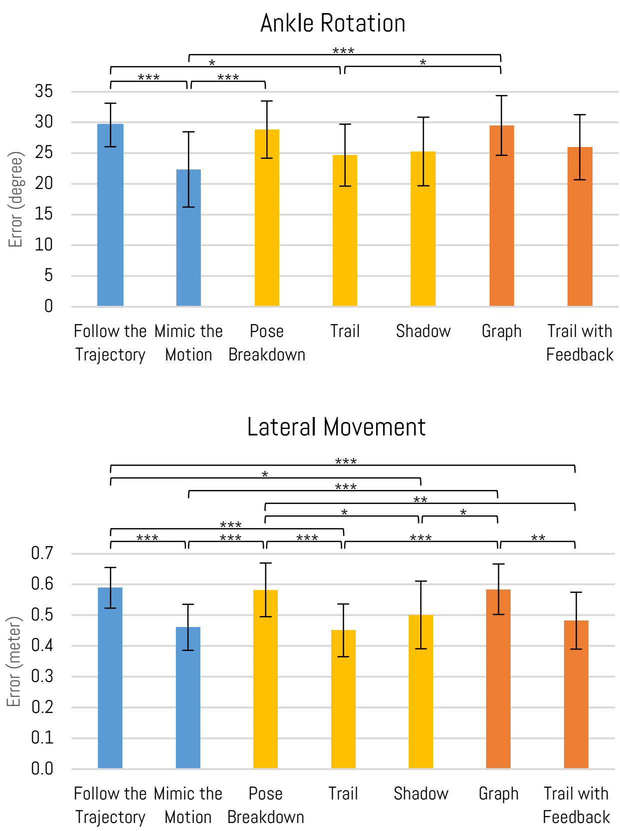

Figure 4. Quantitative results for the Ankle Rotation (top) and the Lateral Movement (bottom). The colors categorize the conditions into expert avatars only (blue), additional visualization (yellow), and integrated feedback (orange), which also correspond to the the three research questions. The brackets on the top indicate the significance between the conditions: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.005$). For example, in case of Lateral Movment, the Trail with Feedback condition is significantly better than Follow the trajectory with $p < 0.005$.

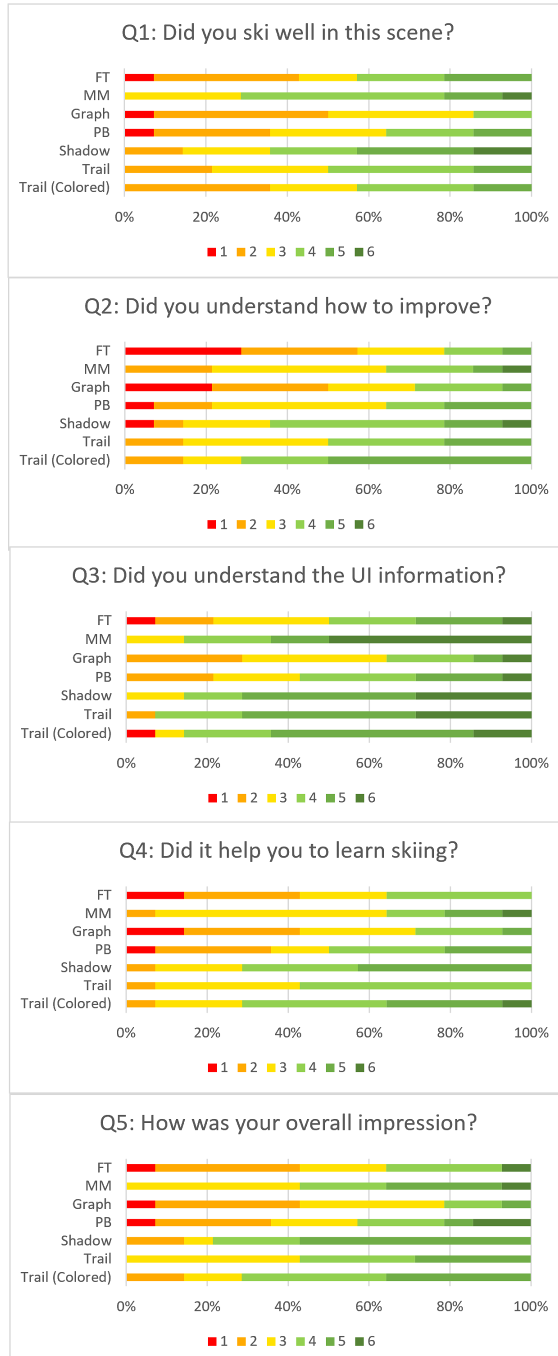

Figure 5. Qualitative Result, these figures show the ratio of the answer of 6-point for each visualization. FT: Follow the Trajectory, MM: Mimic the Motion, PB: Pose Breakdown.

4.5.1 Effect of Real-time Mimicking

Users reported that mimicking the motion felt easier than following the trajectory. Investigating this effect shows that copying the motion of the expert directly, without delay as done in *Mimic the Motion* significantly boosts performance over the more realistic *Follow the Trajectory* condition. Analysis show that users are better in adapting the ankle rotation ($t_{21} = -4.936$, $p < 0.001$) as well as the lateral movement ($t_{21} = -5.069$, $p < 0.001$) of the expert skier. When being asked, which of the two conditions they prefer, almost all users pointed out that they felt that *Mimic the Motion* was easier to perform than the *Follow the Trajectory* condition, which is also reflected in their questionnaire answers, where *Mimic the Motion* was ranked significantly higher than *Follow the Trajectory* for each question (Q1: $Z = -2.331$, $p < .05$, Q2: $Z = -2.319$, $p < .05$, Q3: $Z = -2.464$, $p < .05$, Q4: $Z = -2.001$, $p < .05$, Q5: $Z = -2.313$, $p < .05$). Hence, we can conclude that in scenarios, where the primary focus is in copying a motion, the temporal delay is beneficial and appreciated by the users.

4.5.2 Effect of additional Visual Cues

In our study we compared three conditions that provided additional visual cues in addition to the avatar of the expert: *Pose Breakdown*, *Trail*, and *Shadow* (yellow histogram in Figure 4). To ensure comparability all of them were based on the *Follow the Trajectory* condition. The results show that there was no big difference in ankle rotation between this base condition (*Follow the Trajectory*) ($M = 29.60$, $SD = 3.53$) and the *Pose Breakdown* condition ($M = 29.51$, $SD = 4.84$), as also illustrated in Figure 4 (top). The performances in the *Shadow* ($M = 25.25$, $SD = 5.58$) and *Trail* condition ($M = 24.68$, $SD = 5.05$) were considerably better, with the *Trail* leading to a significantly better result than *Following the Trajectory* ($t_{21} = -3.355$, $p < 0.05$) regarding ankle rotation.

Overall we can conclude that the *Pose Breakdown* condition it is the worst option of the tested conditions, as also its performance regarding lateral movement ($M = 0.58$, $SD = 0.09$) is only marginally better than the base condition ($M = 0.59$, $SD = 0.11$). However, as shown in Figure 4 (bottom), the lateral movement measures show that the participants performed significantly better in the *Shadow* condition ($M = 0.50, SD = 0.11$) in comparison to *Follow the Trajectory* ($t_{21} = -3.483$, $p < 0.05$) and *Pose Breakdown* ($t_{21} = -3.235$, $p < 0.05$). The performance in the *Trail* condition ($M = 0.45$, $SD = 0.09$) was even highly significantly better than *Follow the Trajectory* ($t_{21} = -5.451$, $p < 0.001$) and *Pose Breakdown* ($t_{21} = -5.203$, $p < 0.001$).

The opinions of the participants were more controversial, some users stated that the cloned avatars in the *Pose Breakdown* condition were their preferred visual cue, describing it as *"intuitive"* (P6) and *"easy to understand"* (P10, P11) but also as *"making me a little scared"* (P10, P14). However, the questionnaire results rating how understandable the information was (Q3), shows a significant preference for *Trail* over *Pose Breakdown* ($Z = -2.153$, $p < .05$). Overall, the *Trail* condition was perceived quite positively as it was *"easy to know the [target] position"* (P4), and *"helpful to make the orientation clear"* (P13). Similar to the *Shadow* condition, which made it *"easy to understand the posture of the whole body to be taken"* (P12), and was also described as *"simple and easy"* (P5). One repeated problem that was reported for *Trail* and *Shadow* was the need to look down (P5, P7, P9, P13).

In conclusion, due to the strong quantitative results, the Trail shows the greatest potential for improving the capability of the participants. However, the *Trail* only works well when the trajectory is followed in a realistic way. This means it cannot be easily paired with the *Mimic the Motion* condition, which has the best performance regarding ankle rotation ($M = 22.36, SD = 6.13$) . This could be a chance for the *Shadow*, which is more flexible in this regards and performed almost as well.

4.5.3 Effect of direct feedback

The visual aids discussed above do not provide any direct feedback of the users' own performance. While many of the participants appreciated feedback in general, they specifically disliked the *Graph*, considering it *"hard to understand"* (P4) and *"better for replay"* (P7). Given the performance results of this condition (ARot: $M = 29.51$, $SD = 4.86$; LMov: $M = 0.58$, $SD = 0.08$) there are valid reasons for this as despite the explicit display of the ankle rotation the performance of this parameter is significantly worse than in *Trail* ($t_{21} = 3.293 p < 0.05$) and even highly significantly worse than in *Mimic the Motion* ($t_{21} = 4.874$, $p < 0.001$). Also regarding the lateral movement the Graph condition performed rather poor. *Shadow* ($t_{21} = -3.301$, $p < 0.05$), *Trail* ($t_{21} = -5.270$, $p < 0.001$), and *Mimic the Motion* ($t_{21} = 4.887$, $p < 0.001$) performed significantly resp. highly significantly better.

While performing relatively well in comparison to most other conditions, the performance of the *Trail with Feedback* condition (ARot: $M = 25.97$, $SD = 5.29$; LMov: $M = 0.48$, $SD = 0.09$) is not quite as good as in the *Trail* condition for both metrics. However, it is still significantly better than the *Graph* when considering lateral movement ($t_{21} = -4.024$, $p < 0.01$). Most participants preferred the *Trail with Feedback* over the *Graph* as it is *"relatively intuitive"* (P4, P6), but also stated that it is *"hard to know the exact value of the angle to change"* (P7). This impression is backed up by the questionnaires that show that participants ranked *Trail with Feedback* significantly higher than *Graph* in all categories but Personal Performance (Q1): Q2: $Z = -2.577$, $p < .01$,Q3: $Z = -2.250$, $p < .05$, Q4: $Z = -2.608$, $p < .01$, Q5: $Z = -2.116$, $p < .05$.

These results suggests that additional feedback (at least as provided in our conditions with short adoption time) is not always helpful as it draws some attention, which might be better spent focusing on the task.

5. Discussion

Performing qualitative and quantitative evaluations on visualizing expert ski motion provided us with a number of interesting insights and surprising results. The results show a unexpectedly clear picture about the performance benefits of directly mimicking the expert motion in contrast to the more realistic experience of following the expert's path, when there is no additional visual support (e.g. Trails) but also overall. This suggest that in conditions where there is a smooth slope without bumps and other obstacles and a predictable motion pattern to follow, copying motion directly seems to be the best option. For less predictable motions considering a slight delay might be advantageous to account for some reaction time.

Another surprise was that the performance measures of the *Pose Breakdown* condition showed a much clearer picture than the controversial discussions about it in the first evaluation. Its performance is considerably worse than comparable conditions, such as *Trail*, *Shadow*, which shows that our developments went into the right direction. We assumed that the *Trail* would do well regarding lateral movement, but we were positively surprised that users still had a good performance regarding ankle rotation.

How to provide feedback in the dynamic context of a ski simulator is quite challenging. While the results could be interpreted that providing feedback almost has a negative effect, our two conditions might be to little to make a final call on that. In general there are two aspects to a feedback mechanism: 1) to provide information about the performance (i.e. if you as a user are doing well), and 2) to provide information about how to optimize your performance. While the first aspect was well covered in the *Trail with Feedback*, the second one was not addressed at all. The *Graph* addresses both aspects, however, its complexity makes it hard for users to effectively use the feedback. We assumed that participants might be more positive when they had some time to get familiar with the visualization in a training session as we ourselves got used to it during development, however, this was not the case. Maybe more complex and fine-grained feedback mechanisms require more learning time to become useful.

In summary, we can conclude that in scenarios where it is possible to directly mimic the motion this is the most promising approach. The performance without additional visual cues was more than competitive in comparison to all other tested approaches. Even though not tested directly, a combination with the *Shadow* condition could be considered. In the case that the circumstances require an implementation based on *Follow the Trajectory*, using a *Trail* is the best option. Based on the current results, implementing feedback does not necessarily provide benefits and therefore needs to be carefully considered.

6. Conclusion and Future Work

In this work we present a VR-based ski simulator that provides users with an immersive skiing experience and helps to overcome environment restrictions of alpine ski training using comparatively cheap equipment. With the goal to train users with prerecorded motion from professional athletes, we examined different ways to visualize expert movement to support training by copying the motion. In an initial pilot study performed in a VR conference, we collected a large number of responses that helped us to gain insights on the visualizations. In the subsequent controlled experiments, we collect quantitative and qualitative data and compared the performance of the 6 visualizations in order to get a better understanding of the implications of certain design decisions.

As a result, these evaluations showed that when learning from expert motion in a VR-based ski simulator, mimicking the motion of the experts directly leads to better performance then following the trajectory of the skier as it is common practise when learning skiing on a real-world ski slope. When this is not possible, a special trail visualization, which is rendered as a ribbon to also show the ankle rotation showed a runner-up performance. The evaluation also indicates that providing feedback on the users performance during the practise is not necessarily improving the performance.

This information about what kind of representations perform best help to increase the effectiveness of the VR ski simulator as a training device. In addition, they provide the basis for a future evaluation of effectiveness of this training method. In the future we are interested in investigating if the copied motions leads to a lasting change of the users' movement patterns. However, the positive feedback of the users in the conducted evaluations already suggest that the presented approach provides suitable complementing alternative to current training methods in alpine skiing

Besides this, there are also a number of improvements that can be applied directly to the system that we would like to test in the future. To keep the system simple we currently do not use additional sensors or trackers on user's body and purely rely on the tracking of the skies for performance measurement. As ski racers confirmed that the foot angle is a significant factor in alpine skiing this seems like a good compromise. However, in the future, we would like to extend the tracked features, so that we can also analyze the center of gravity and other factors for a more precise performance metrics.

Acknowledgment

This work was supported by JST CREST, Japan, under Grant No.: JPMJCR17A3.

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