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Learning Support and Evaluation of Weight-shifting Skills for Novice Skiers Using Virtual Reality*

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Abstract. In this study, we propose a virtual reality learning support system designed to help train novice skiers. In previous research, we extracted the differences between the weight shifting movements and skiing postures of experts and beginners using deep learning. The obtained results showed weight shifting to be a more important feature than posture. Accordingly, we focused on supporting the weight-shifting technique. The support system provides real-time feedback to a user on their current weight-shifting status. We conducted an experiment to verify the effectiveness of the proposed approach, in which we defined evaluation criteria for a user's level of skiing proficiency. The experimental results demonstrate that the system successfully facilitated participants' acquisition of the weight-shifting skill.

Keywords: Ski · Learning support · Virtual reality · Visual feedback · Deep learning.

1 Introduction

Computer-assisted training systems for sports have been presented in several studies[5, 13]. These systems analyze a user's performance in terms of measured data, and compare data of novice and expert users to determine the differences.

In this study, we focus on the development of a learning support system for skiing. Some ski-training systems for beginners do exist[8, 18], although most are designed for intermediate and advanced users[3, 6]. Moreover, existing support systems do not support communicate or display the differences between the movements of user and expert in real time.

Prior to the development of the learning support system, we extracted the differences in the weight shifting and posture of experts and beginners in a virtual reality training system to identify the most important skills required to learn to

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ski[2]. We classified 11 participants based on their posture and weight shifting using Darknet-53[12] to extract features. Results obtained from Grad-CAM[15] indicated that weight shifting affected the classification more than posture. This result supports previous findings, such as balance test comparisons conducted before and after participants learned to ski[17].

Accordingly, we focused on weight-shifting technique in this work. Hence, we proposed a method designed to support learning the weight-shifting skills used in skiing with an awareness of the current status of the user's gravity center in real time. As part of the proposed approach, we implemented a visual feedback process to display the differences between the gravity center of a user and an expert. Moreover, we defined evaluation criteria to distinguish proficiency levels based on user performance to verify the effectiveness of the system.

2 Related Research

Several existing systems have adopted various methods to provide awareness of certain techniques to users. Heike and Ohgi[3] developed a ski-jump training system using deep learning. This system extracted a user's posture and the V-angle of their skis from inertial sensor data, and divided them according to each ski-jump phase. The system then extracted features from these data and compared them using a deep-learning model. Moreover, Fasel et al.[6] proposed an alpine skiing training system. In addition to multiple inertial sensors, this system utilized magnetic sensors placed at each gate to estimate the posture of a user.

Such methods have also been explored in other sports. For example, Sato and Tokuyasu[13] developed a pedaling-skill training system for cyclists using principal component analysis. The authors established evaluation criteria based on the muscle-activity data of skilled cyclists, and the system compared them with muscle-activity patterns extracted from a user via principal component analysis. Moreover, Chen et al.[5] developed a yoga training system using image recognition. This system compares feature points obtained from user data including skeletons and contours, topological skeletons, and main axis with those obtained from experts.

These systems analyzed a user's movement and compared them with those of an expert to help users improve their technique. In particular, existing skiing learning systems[3, 6] do not provide feedback in real time because they are designed for advanced users who are able to improve their skills even without real-time feedback.

However, although these methods can inform users as to their technique and may increase users awareness of their form, they do not always help users to acquire the technique. In particular, it is difficult for beginners to acquire skills purely by receiving information on the differences between the techniques of beginners and experts. Therefore, in this study, we adopt real-time feedback to facilitate natural learning.

As a training system using real-time feedback, Hasegawa et al.[8] presented a skiing training system for beginners. The system enabled real-time correction of the positions of both feet using auditory feedback. This system measures the center of gravity of users' feet as they move forward. The system varied the pitch of the sound depending on these positions to inform a user as to the position of their feet.

However, this system was developed for actual skiing sites. Due to seasonal and geographical limitations, it is difficult to practice skiing at any arbitrary time and place. Consequently, learning-support environments for beginners are often insufficient. Hence, we adopted a virtual reality training environment in this work.

3 Development of a Ski Learning Support System

The proposed system is based on a previously developed approach[18]. The movements of an expert skier are displayed to the user via a virtual reality training system to guide them to adjust their movements to match those of the expert. We adopted the same virtual reality system (HTC Vive Pro[1]) and ski simulator (Pro Ski-Simulator: POWER SKI SIMULATOR[2]).

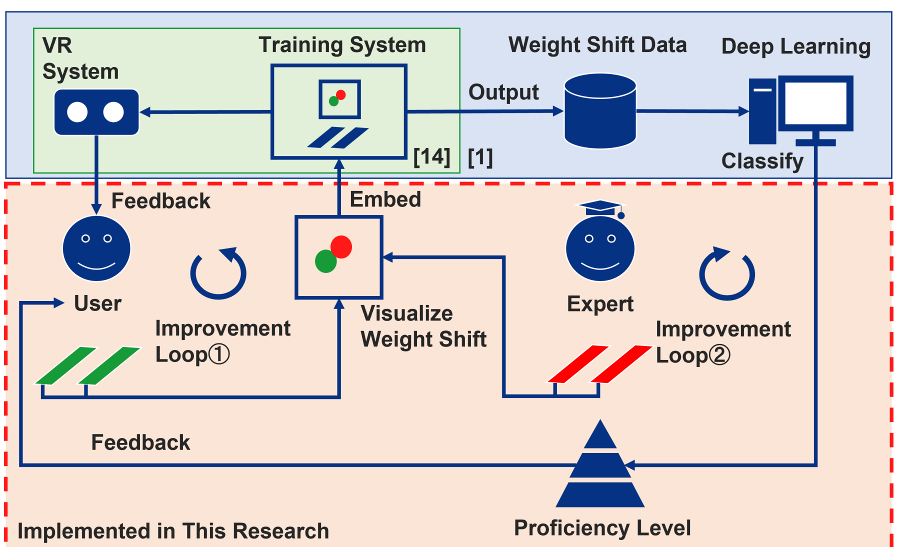

Fig. 1. Proposed system: This research implemented short and long-term improvement loop systems in the existing system.

[1] https://www.vive.com/eu/product/vive-pro/
[2] https://www.ski-simulator.com/power-ski-simulator-en

Figure 1 illustrates the proposed system. Overall, it comprises two loops to help beginners acquire the target skill, including a short-term loop (improvement-loop 1) and a long-term loop (improvement-loop 2). In the short-term loop, the system provides visual feedback to the user via a virtual reality training system in real time as they shift their weight. This enables beginners to become more aware of the difference in how they shift their weight compared to the technique demonstrated by the experts. In addition, in the long-term loop, the system provides the user's proficiency level in the current trial based on the classification results obtained by deep learning. This helps beginners consolidate their weight-shift skills.

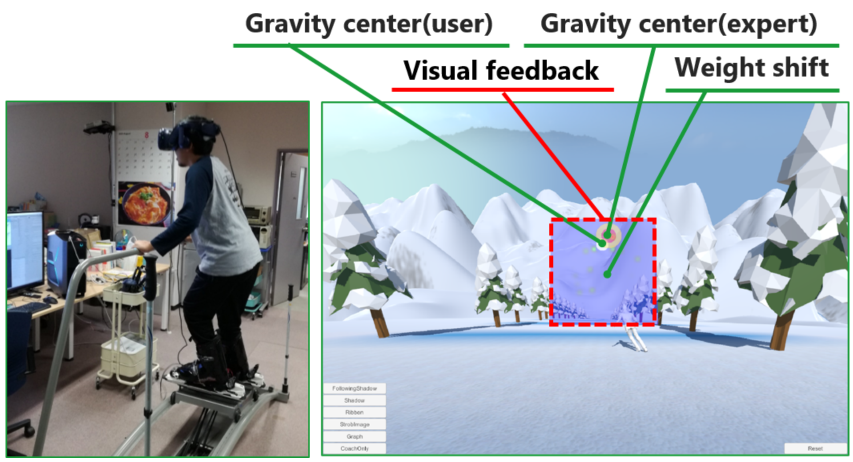

Fig. 2. Condition of the users while using the system

Figure 2 illustrates the conditions of users while using the system. In this study, we adopted visual feedback because it is effective in weight-shifting [11] and balance training[10, 14]. The system includes a feedback layer displaying the user's current skiing status, which includes the user's weight shift and center of gravity, along with an expert's center of gravity. Accordingly, the user can instantaneously recognize all the relevant information simultaneously at a glance, without moving their eyes.

Figure 3 shows the pressure sensor module. In the proposed system, data on users' weight shifting are collected by 16 pressure sensors attached to the soles of ski shoes and transmitted via a wireless network. In a previous work[2], we used eight pressure sensors on each sole. These sensors were based on the system of Fukahori et al.[7]. However, their system focused on the approximate recognition of foot gestures, mainly toes and heels. Therefore, to measure the weight shift data more finely and accurately, we used double the number of sensors attached in previous research[2]. To implement this improvement, we used a

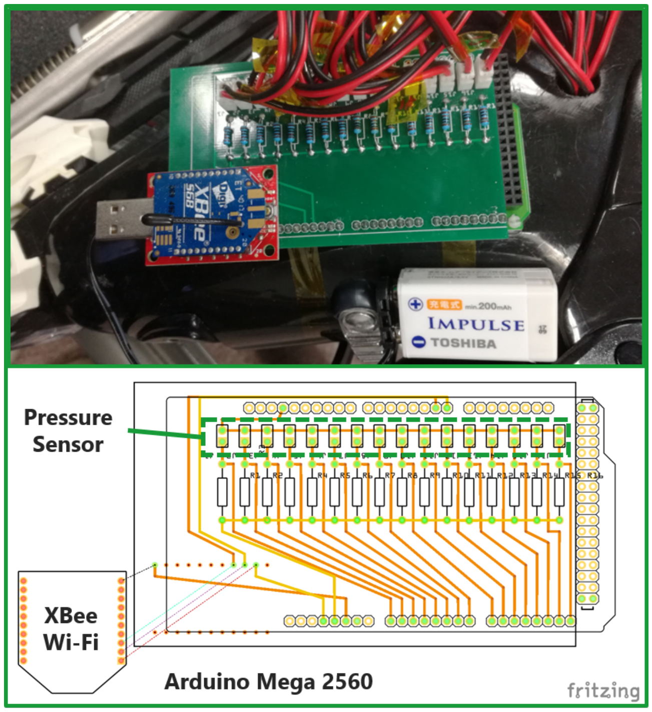

Fig. 3. Pressure sensor module

compatible Arduino Mega 2560 microcontroller (What's Next Green) instead of the older alternative (an Arduino Fio-compatible Sparkfun Fio v3ATmega32U4). Furthermore, in contrast to the previous module, the new module was able to drive with a battery by sending data via a wireless network using an XBee S6B Wi-Fi module.

4 Evaluation Experiment

We conducted an experiment to evaluate the efficacy of the proposed system.

4.1 Measurement Methods

As noted above in Section III, the system allows users to observe the movements of experts via a virtual reality training system. In the experiment, participants used the system for one minute and were required to adjust their movements to match those of the expert. The participants used the system three times in each measurement, and we adopted the second and third attempts as data to perform classification.

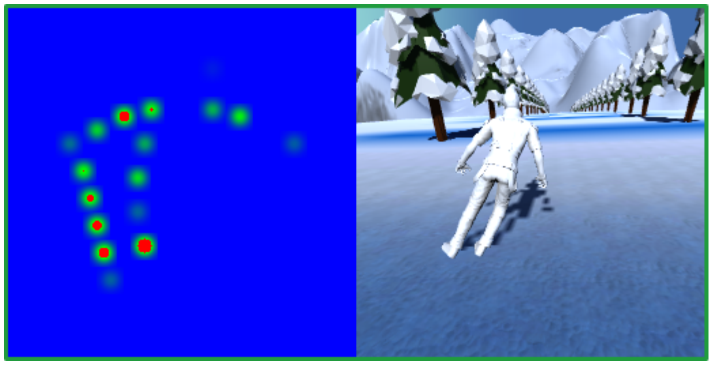

Fig. 4. Example of outputted image

To classify users using deep learning, the system outputs an image combining the user's weight shift and the expert's posture data, as presented in Figure 4. In our prior research[2], we correctly classified 11 participants into four proficiency levels based on their skiing experience and turning method. In the present work, Darknet-53[12] was adopted to perform feature extraction.

4.2 Participants

Initially, we measured the weight-shift data of 16 participants to configure the user experience level classifier, similar to approach adopted in the previous study[2]. Table 1 presents the participants' skiing experience and turning method.

At this point, we classified nine skiers able to perform snowplow turns and five beginners into four experience levels according to their number of days of experience: 0 days (F, J, K, L, M), 1–9 days (A, B, G, I, N, P), 10–49 days (E, O), and 50 days or more (D). Skiers who habitually performed parallel turns (C, H) were excluded to eliminate the influence of differences in turning methods.

4.3 Verification Method

We divided the beginners into two groups according to whether they used the system; participants J, L, and M used it while F and K did not. The participants did not have snowboarding experience, and exercised with a frequency of once a week or less. We measured the users' weight-shift data two to three times per week, for a total of eight sessions.

Eventually, we obtained 37 693 images of weight-shift data from both the skiers and beginners. A total of 23 991 images were used as training data, and the remaining images were used as testing data.

Table 1. Participants of The Evaluation Experiment

ID	Skiing Experience	Turn Method	Used System
A	4 days	Snowplow	Excluded
B	3 days	Snowplow	Excluded
C	above 100 days	Parallel	Excluded
D	above 50 days	Snowplow	Excluded
E	above 10 days	Snowplow	Excluded
F	None	None	No
G	3 days	Snowplow	Excluded
H	above 20 days	Parallel	Excluded
I	5 days	Snowplow	Excluded
J	None	None	Yes
K	None	None	No
L	None	None	Yes
M	None	None	Yes
N	1 day	Snowplow	Excluded
O	above 10 days	Snowplow	Excluded
P	3 days	Snowplow	Excluded

4.4 Evaluation

We define "proficiency level" as the rate of image data misclassified as non-beginner in each session, as given below.

$$Proficiency\ level = 1 - \frac{Data\ classified\ as\ 0\ days}{All\ data}$$

For example, we obtained 100 images from a user in one measurement, of which 50 were classified as "0 days," such that their proficiency level was recorded as "0.5." We applied this equation to beginners. Changes in users' proficiency levels over time were used to ascertain whether the participant were able to acquire the weight-shifting skill. Higher proficiency levels indicate that the performance of the user is closer to the weight shift of experienced skiers. Hence, a proficiency level of "1" indicates that the user has progressed beyond the skill level of a beginner. In this research, users reaching a proficiency level of 1 indicates that they were able to acquire the weight-shifting skill successfully.

However, to help users improve their skills, expert examples must be selected carefully. If the expert's example was excessively close to the users' level, they the users were unable to sufficiently improve their skills. Conversely, if the expert example was excessively far from the users' level of skill, the users were unable to sufficiently realize the experts' technique. In this research, we used participant D's weight-shift as expert data because they were the most experienced in the basic snowplow turning method.

4.5 Result

Figures 5 and 6 present the recorded proficiency levels of users against each group's number of practice sessions. The dotted lines in these figures represent linear approximations of the change in each participant's proficiency level with increasing numbers of sessions.

The group that did not utilize the proposed system did not always exhibit an improvement, whereas all participants in the group that utilized the system showed an improvement. Therefore, the proposed system may be considered effective in facilitating the acquisition of weight-shifting skills by beginners with no skiing experience.

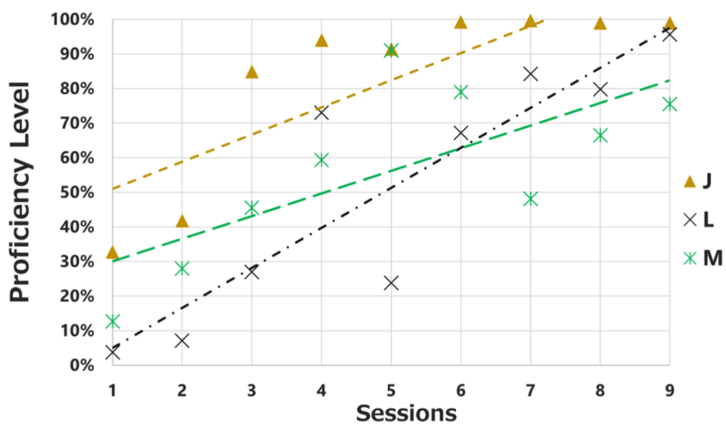

Fig. 5. Change in proficiency level (with the proposed system)

5 Discussion

5.1 Findings

The experimental results show that the feedback provided users with an awareness of how to improve their weight-shifting skill. However, in the group that utilized the proposed system, the proficiency levels of participants exhibited greater variably than those of other groups. The presented expert's data was only composed of gravity center collected from 32 pressure sensors. Therefore, even if a user's center of gravity was same with that of the expert, the actual pressure pattern may differ. This suggests that they improved their weight shifting skill via trial and error to determine how they should move to adjust more easily to the expert's center of gravity. Although all of the available data from the expert could be displayed, we considered that such feedback would be difficult to understand for beginners. Also, from the result, we observed that excessively

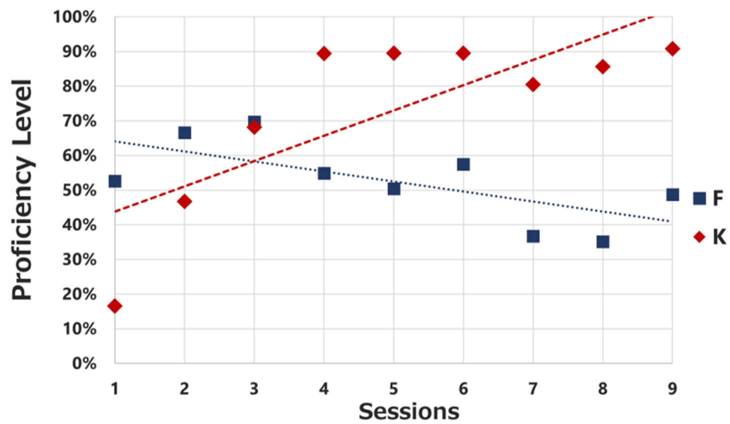

Fig. 6. Change in proficiency level (without the proposed system)

simple feedback reduced the cognitive demands of the system while remaining understandable by beginners. Hence, these results suggest that trade-offs are involved between the fineness, accuracy, and comprehensibility of the feedback.

In contrast, participants that did not utilize the proposed system were not presented with any information to facilitate learning the technique. Therefore, the improvement of each subject' level of skill at weight-shifting skill differed. However, they did learn independently through trial and error. As a result, the proficiency level of subject K was high even without the system. Therefore, the evaluation system proposed in this experiment can support the identification of users with high aptitude.

5.2 Contribution

This type of visual feedback can be used to checking how we are moving. In this research, we focused on supporting users in learning weight-shifting skills. We consider this approach suitable for skills in which it may be difficult to directly recognize the correctness of one's technique. In ski, edging and posture are also important in correctly executing turns. Similarly to the proposed method, supporting edging technique and correct posture can help users to realize improvements in skill by using data from gyroscopic sensors and motion capture to classify their performance.

As another practical use, we can also support correcting strategy in contexts such as racing lines by using time score and sensor data. Although the behavior must be accurately defined, if the relationship between the sensor data and movement are known, unsupervised learning can be used to provide an expert's racing line, and the obtained strategy may differ with the conventional approach (as an example, see Praveen et al.[16]).

This feature can also provide a new approach to skill learning. For example, this feedback and virtual training system can be used to perform distance learning of various skills (Figure 7). Existing distance learning environments remain inadequate[1]. In the case of physical education, it is difficult for instructors to check learners' movements in detail and provide them with direct guidance. This may result in inadequate education. However, as mentioned above, users can check their movement using the proposed system. Then, if the system sends students' measured data to the teacher, the teacher can then evaluate students' movement more easily than with conventional distance learning methods. Similarly, if the system sends the teacher's measured data to the students, they can check their technique against the teacher's. Such direct interaction allows users to acquire skills more easily.

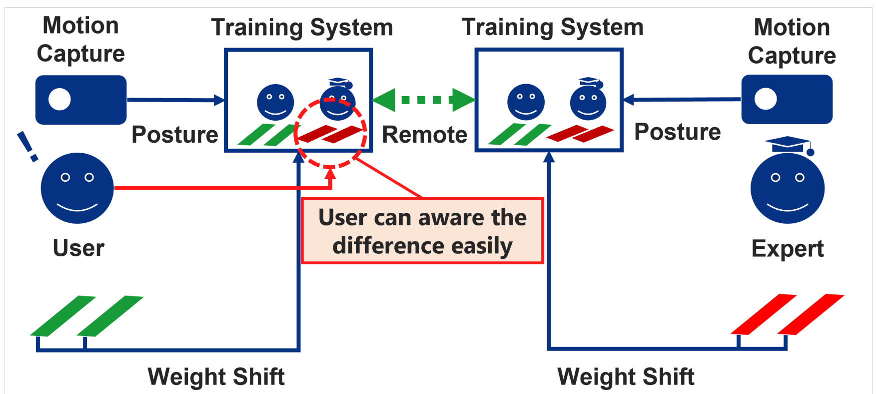

Fig. 7. Distance learning system for ski implemented this system

5.3 Limitation

This research involves the following limitations.

Participants In this study, we focused on supporting beginners in acquiring weight-shifting skills. We used a supervised learning method for classification, and the criteria were only based on the number of days of experience, similar to previous research[2]. Therefore, as a limitation of this method, it was necessary to define the tentative borderline between beginner and non-beginner skiers. Although the previous research classified participants with 0-3 days of experience as beginners, in the present work, we considered participants without skiing experience to classify the difference between their performance and those of participants with some skiing experience. However, some non-beginner participants had not skied for years. It proved difficult for the supervised learning method to determine accurately whether such participants really deserved to be classified as non-beginners.

System In this study, we displayed participant D's weight-shift data statically to simplify the system. However, if the system is applied to all beginners, the amount of support should be adjusted based on users' proficiency. Typically, in creative or physical activities, a user must develop and master skills. For example, children learn to ride bicycles through the following steps. 1) First, they ride with training wheels. 2) Then, they might ride without training wheels while someone holds the seat. 3) Finally, the helper must eventually release the seat when the child starts pedaling. Similarly, we consider that the amount of support should be adjusted according to users' levels of proficiency. In fact, in educational contexts, some research has explored gradual learning[4, 19].

Experiment In this research, we only experimented with a ski simulator. Moreover, we focused on supporting the weight-shifting technique among various skiing skills. Therefore, the proposed system remains insufficient to practice skiing optimally on actual skiing sites. However, the results of this experiment and other studies[9] suggest that that ski training with simulator is effective.

6 Conclusion

In this study, we have developed a learning support system to help novice skiers in acquiring the weight-shifting skill by adopting visual feedback using a virtual reality ski training system. In the experiment, we have defined an evaluation criteria for user proficiency levels and verified that the proposed system was effective in facilitating skill acquisition by beginners. The results indicate that this system successfully helped participants achieve this objective.

In future research, further verification will be required with a larger number of participants and a longer duration to further verify the results. As the first step in this investigation, we focused on learning weight-shifting skill in the present work. However, other elements are also involved in learning skiing, such as posture and edging techniques. Hence, we plan to support these elements using the proposed method.

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