Climbing with Virtual Mentor by Means of Video-Based Motion Analysis

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Abstract: Due to the growing popularity of climbing, research on non-invasive, camera-based motion analysis has received increasing attention. While extant work uses invasive technologies, such as wearables or modified walls and holds, or focusses on competitive sports, we for the first time propose a system that automatically detects motion errors that are typical for beginners with a low level of climbing experience by means of video analysis. In our work, we imitate a virtual mentor that provides an analysis directly after having climbed a route. We thereby employed an iPad Pro fourth generation with LiDAR to record climbing sequences, in which the climber's skeleton is extracted using the Vision framework provided by Apple. We adapted an existing method to detect joints movements and introduced a finite state machine that represents the repetitive phases that occur in climbing. By means of the detected movements, the current phase can be determined. Based on the phase, single errors that are only relevant in specific phases are extracted from the video sequence and presented to the climber. Latest empirical tests with 14 probands demonstrated the working principle. We are currently collecting data of climbing beginners for a quantitative evaluation of the proposed system.

1 INTRODUCTION

In recent years, climbing has become a **mainstream sport**. Due to this popularity of climbing, but also due to increasing computing power of mobile devices and enhanced sensor technologies, climbing motion analysis is an increasingly investigated research topic. To date, **existing work** has investigated the use of sensors integrated into the wall and the holds, body-worn sensors, or camera-based, non-contact sensor technology, to name several examples, which are also cited in Section 2. So far, however, there exists no application that, on the basis of video analysis, analyses a climber's pose to **automatically detect motion errors for beginners**. In view of climbing becoming a mainstream sport, such a system would be helpful to teach persons without or limited climbing experience correct techniques that would normally be introduced by a trainer.

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In our study, which is still work in progress, we propose such a system, i. e. a **virtual mentor**, that based on a skeleton model segments a climber's motion into typical repetitive climbing phases and subsequently automatically analyses the motion in terms of technique errors occurring in these phases that are typical for beginners.

The paper is structured as follows: Section 2 reviews previous work, followed by an excursion into the theory of climbing in Section 3. Thereupon, Section 4 introduces the sensor setup, reviews existing skeleton detection algorithms with respect to their suitability for climbing applications, and explains our system components. The developed application that was tested in first empirical evaluations with 14 probands is presented in Section 5. A summary and an outlook are given in Section 6.

2 RELATED WORK

When considering previous work related to systems developed in climbing applications, we can group the employed sensors into three main groups:

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- Instrumented climbing walls, where sensor technology is integrated in the wall or in the holds such as strain gauges e. g. (Quaine et al., 1997a), (Quaine et al., 1997b), (Quaine and Martin, 1999), force torque sensors e. g. (Aladdin and Kry, 2012), (Pandurevic et al., 2018), and capacitive sensors e. g. (Parsons et al., 2014).
- Body-worn sensor technology such as body-mounted acceleration sensors e. g. (Ebert et al., 2017) , (Kosmalla et al., 2016), (Kosmalla et al., 2015), and visual markers e. g. (iROZHLAS, 2019), (Cordier et al., 1994), (Sibella et al., 2007), (Reveret et al., 2018)
- Camera-based, non-contact sensor technology, e. g. (Pandurevic et al., 2022)

Camera-based approaches offer the advantage that they are easy to integrate into a climbing setup without having to change holds or the wall itself, for example. Furthermore, they work contactless, so that the climber does not have to wear additional equipment, which has to be attached on the body, may restrict the movements or may also lead to injuries (wristbands). Moreover, the increasingly high-quality cameras integrated in mobile devices offer new possibilities for climbing applications.

In the following, a selection of very early as well as most recent camera-based approaches for climbing motion analysis and feedback systems are presented.

A very early work is the marker-based approach by (Sibella et al., 2007). They demonstrated that it is possible to compare entropy, velocity, and induced force of climbers by tracking markers taped to the climber's body with a camera and calculating the body's centre of gravity from these markers.

In lead climbing, Adam Ondra and Štěpán Stráník were equipped with reflective markers and thus analysed via a commercial motion capture system (iROZHLAS, 2019). The centre of gravity was determined for both climbers and their distance from the wall was compared. It became clear that Adam Ondra keeps his centre of gravity significantly closer to the wall during a difficult move than Štěpán Stráník.

In speed climbing, a very recent work (Pandurevic et al., 2022) demonstrated the application of OpenPose (Cao et al., 2018), (OpenPose, 2019). By measuring body joint angles, velocities, contact times and path lengths, they compared speed climbing techniques of top athletes and identified potential for improvements.

Reveret et al. investigated energy losses in speed climbing caused by non-upward climbing sequences, i. e. lateral and horizontal components (Reveret et al., 2018). For this purpose, they used two drones equipped with cameras to analyse climbing movements in speed climbing in terms of the energy used in the form of velocities. This involved the climber wearing a harness with a visual marker, which was localised in three dimensions by the two drone cameras. The trajectories of the markers were recorded so that the velocity components could subsequently be measured in the vertical, lateral and horizontal directions.

Kosmalla et al. presented a system for visualising reference motions on a bouldering wall (Kosmalla et al., 2017). They calculated the climber's centre of gravity from the 3-D skeleton provided by the Kinect v2 in order to determine the location of the projection onto the wall. The combination of sensor and projection unit is called betaCube there. Their work resulted in the Climbtrack assistive technologies for sports climbing, which is available with the betaCube (ClimbTrack, 2019).

A more detailed overview about sensors, motion capture, and climbing motion analysis algorithms is provided by (Richter et al., 2020).

3 CLIMBING THEORY

During climbing up a route, the three phases **reaching**, **stabilisation** and **preparation** appear repetitively. An ideal climbing motion sequence is characterised by the following procedure: Reaching means that the climber shifts his weight to one of his legs, stands up over this leg while reaching to the next hold with one hand. This reaching hand becomes the holding hand. After the climber has gripped the hold, he is in the stabilisation phase, where he ideally lowers his body. Then he is able to look for next holds in a rather comfortable position. From the stabilisation phase, the climber either re-sets the feet to prepare the next reach resulting him to transit to the preparation phase, or directly reaches to the next hold without re-setting the feet resulting in a transition back to the reaching phase. From the preparation phase, the climber goes to the reaching phase once the feet are finally set. Moreover, the hip and one hand start moving. The phases with their characteristics are summarised in Figure 1 in the green bubbles. Additionally, the items in the gray boxes indicate the techniques a climber should pay attention to during the respective phase.

Especially for beginners, **motion errors** are common. Hereby, each error can be attributed to a specific phase and shall only be detected in this very phase. This will be explained on an example in Section 1. In Table 1, the correct techniques and the errors that

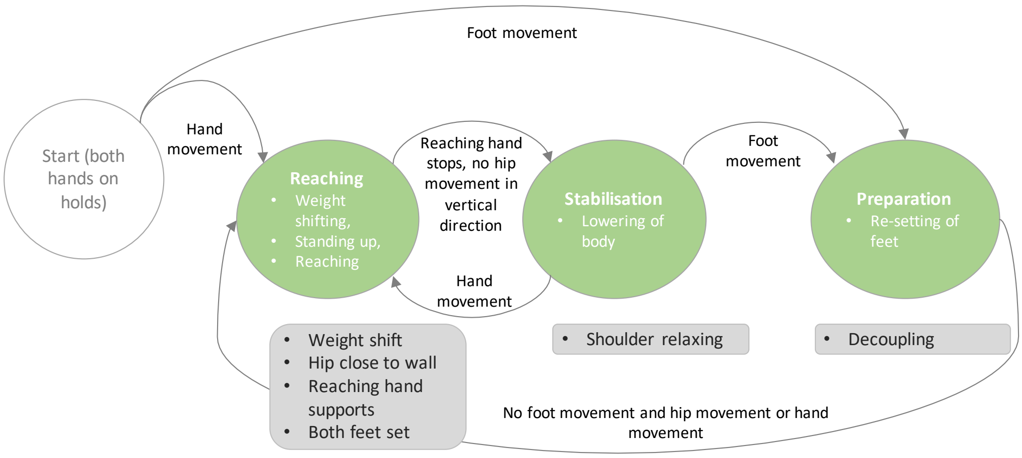


Figure 1: Climbing phases with their characteristics (green bubbles), according techniques (gray boxes), and transitions between the phases that are based on hand, foot and hip movement.

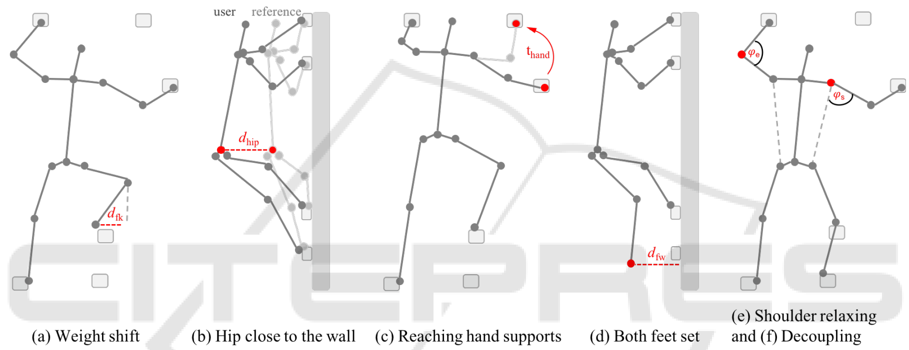


Figure 2: Principles of error detection. (a), (b), (c), (d), (e) and (f) correspond to the errors described in Table 1.

occur are described. These errors occur when a specific technique is not performed correctly. Additionally, Figure 2 presents a visual summary of typical errors that we detect while a climber is in a route.

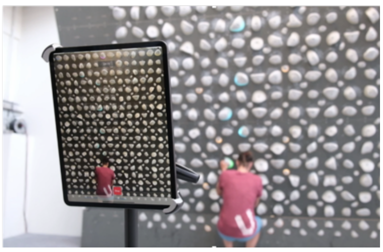


Figure 3: System setup with iPad Pro.

4 METHODS

The following sections present the components of the developed feedback system.

4.1 Setup and Sensor

In our study, we employed the iPad pro fourth generation, which provides a light detection and ranging (LiDAR) sensor that enables depth measurements in our case at 60 frames per second. From this depth information, a 3-D point cloud with a dense grid can be calculated. Next to sensor data provision, the iPad itself also serves as a computational and visualisation unit where the sensor data is processed and the feedback is prepared for the climber. Figure 3 illustrates the setup of our system. The iPad can be installed at an arbitrary location in front of the wall, optimally in at a distance of four to six metres. Within that range, the whole wall is visible in our setup while the LiDAR depth information is still reliable. During one single route recording, the position should remain fixed.

Figure 4 exemplarily shows the 3-D point cloud provided by the iPad. This point cloud is used for 3-D skeleton extraction and extrinsic camera calibration, which is explained in the following sections.

Table 1: Description of correct execution and climbing errors.

Name of correct technique	Correct execution description	Error description
(a) Weight shift	While standing up, the weight is shifted over one leg (normally the leg opposite the holding hand), the knee moves vertically in front of the toe of that leg, the hip goes first over the leg and then upwards. In that way, the main power origins from the large leg muscles and not from the smaller arm muscles.	The climber does not shift the weight over the supporting leg and stands up while pulling on the arm.
(b) Hip close to the wall	When the climber moves his or her weight upwards, the main weight should remain on the supporting leg. This can be realised by keeping the hip close to the wall. In that way, the main weight rests on the legs and does not pull on the arms.	The hip is far away from the wall, resulting is the body weight pulling on the grips held by the hands.
(c) Reaching hand supports	The reaching hand should support the process of standing up as long as possible to stabilise the body and to save energy. The reaching process should not take longer than one second.	The reaching hand leaves the hold too early.
(d) Both feet set	While standing up, both feet should have contact to the wall because it stabilises the body.	Only one foot has wall contact.
(e) Shoulder relaxing	After reaching, the climber should lower his or her position again so that the arms are as straight as possible. This position saves energy.	After reaching, the climber remains in the position where the arms are probably bent.
(f) Decoupling	When placing the feet, the climber shall keep the arm of the holding hand as straight as possible to save energy.	The climber bends the arm of the holding hand resulting in an unfavourable load on the grip, which requires more strength.

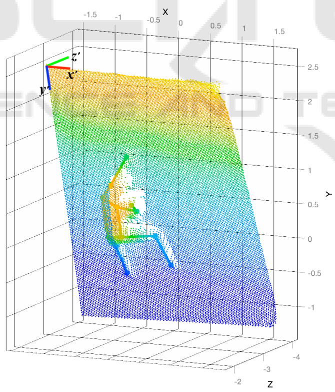


Figure 4: 3-D point cloud with wall coordinate system at the top left corner of the wall and extracted 3-D skeleton.

4.2 Skeleton

In a pre-study, together with a partner that potentially will use the developed system, we **reviewed several skeleton extraction algorithms** including NUITRACK (NUITRACK, 2022), OpenPose (OpenPose, 2019), PoseNet (GitHub, 2021), (Papandreou et al., 2018), Apple Vision (Apple, 2022b) and Apple ARKit (Apple, 2022a). We found that NUITRACK, PoseNet and Apple ARKit are unsuitable for climbing applications since they are inaccurate when the person is viewed from behind and occlusions as well as non-conventional poses are present. Still, PoseNet can be re-trained with climbing poses. Considering OpenPose, it was found to be suitable, but companies are facing licencing problems when they want to use it commercially. OpenPose is free of licence only for academical use. That is why we decided to use the **Vision framework** by Apple (Apple, 2022b), which provides a 2-D skeleton suitable for climbing pose detection. A profound review on 3-D human pose estimation is provided by (Desmarais et al., 2021).

The iPad provides the opportunity to extract a 2-D skeleton from the RGB image data. By means of the Vision framework, 19 body features can be detected, as illustrated in Figure 5. To obtain a 3-D skeleton for view-invariant motion analysis, we **calculated the 3-D joint coordinates** for relevant by means of the 3-D point cloud: A 2-D joint is converted into 3-D wall coordinates and its neighbouring points are averaged to calculate the final joint coordinate. For the transformation of 2-D joints detected in the RGB image to 3-D joints in world coordinates, a calibration is performed. An example of a calculated 3-D skeleton is shown in Figure 4. Relevant joints for our climbing evaluation are ankle, knee, elbow, wrist, shoulder and hip joints as well as the root. In the following, the wrist is denoted as hand and the root as hip.

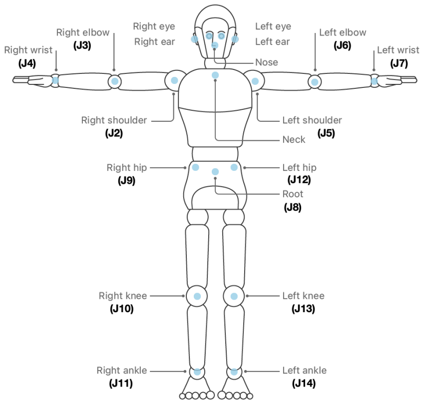


Figure 5: Vision skeleton, (Apple, 2022b).

4.3 Camera Calibration

The aim of the calibration is the **representation of 3-D joint coordinates with respect to a wall coordinate system**. This wall coordinate system is defined by an origin at the top left wall corner while the x-y plane represents the wall surface and the z component the distance from the wall, see Figure 4. Moreover, the calibration is necessary to enable an alignment with a reference recording available for every route and a user recording in order to compare both with respect to motion errors. Furthermore, the representation of the hand joints in wall coordinates is used to automatically detect the climber on the start holds.

The orientation of the coordinate system is determined by firstly detecting the largest plane in the point cloud using the RANSAC algorithm (Fischler and Bolles, 1981). The largest plane defines the x and y axes and the orthogonal vector denotes the z axis. The top left corner, i. e. the origin, is found by segmenting the point cloud of the climbing wall by a 2-D polygonal approximation (Ramer, 1972). This calibration process is performed at the beginning of every route recording, so that the recorded data is view-invariant in case the sensor is re-located. The calibration method works for any rectangle wall, such as Kilter (Kletterkultur, 2019), Moon (Moon Climbing, 2019) and Tension board (Tension Climbing, 2019).

4.4 Movement Detection

Joint movement detection is a **pre-processing step for the subsequent phase detection**. In order to specify in which current phase a climber is, we have to determine which joints are moving, because the phase transitions depend on joint movements, see Figure 1. In particular, hands, feet and the hip are relevant at this point. Joint movement detection is done by projecting the 3-D points of these very joints onto the x-y wall plane. Then, the joint velocity v in mm per second on this plane is evaluated.

Here, we used an adapted version of (Beltrán B. et al., 2022), whereas we calculate the standard deviation σ of the joint velocity with respect to the mean velocity μ within a sliding window instead of an accumulated acceleration. For every joint and frame, the sum of the mean and the according standard deviation $\mu + \sigma$ is then compared against a route-variable threshold thr, which is determined as 40 % of the maximum of the respective joint velocity within the route. For all frames with this higher sum than this threshold the respective joint is considered to be moving. In this case, the algorithm detects the joint to be moving ($mov = 1$), else the joint is assumed to be not in movement ($mov = 0$), as represented in Equation 1.

$$mov = \begin{cases} 1, & \text{if } \mu + \sigma > 0.4 \cdot max(v), \\ 0 & \text{else.} \end{cases} \tag{1}$$

Figure 6 presents the principle of movement detection for an example joint. At the top, the velocity, the mean velocity of the sliding window and the standard deviation along the route are presented. The graph at the bottom illustrates the labeled ground truth and the obtained movement output mov.

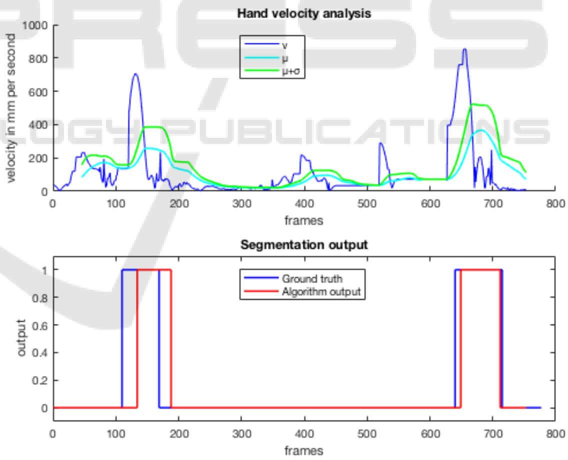


Figure 6: Principle of joint movement detection.

4.5 Phase Detection

Based on the movement information of hands, feet, and hip, the current climbing phase can be determined. In this study, we propose a **finite state machine** that represents the process of climbing movements along a route. It is necessary to know in which phase the climber is, because depending on the phase, only certain errors have to be checked. In the stabilisation and preparation phase, for example, it is important that the holding arm is straight while in the reaching phase it is only natural that it is not straight. Consequently, we only should check for a straight arm in the stabilisation and the preparation phase. Figure 1 illustrates how the **detected movements of the specific joint finally influence the transitions** between the phases.

At the beginning of each route, the climber has to start with both hands on the start holds. To detect this, we evaluate whether both hands are not moving and close to the wall by checking whether the z components of the 3-D wrist joints are within a defined range around the wall plane. Next, we are waiting for either a hand or a foot movement to jump into the reaching or preparation phase respectively. The moving hand is denoted as the next holding hand then. From the reaching phase, the climber transits to the stabilisation phase when the hand stops on the hold and no vertical hip movement is detected any more. It is possible to jump back to the reaching phase in case of new hand movements. Otherwise, once a foot movement occurs, the climber is considered to be in the preparation phase where he or she re-organises the feet. Once no foot movement is measured because the climber has finished re-setting the feet or a hand movement to the next hold is detected, we jump to the reaching phase. For the foot movement, we additionally check whether there is a hip movement. Only checking for the feet to be at rest would not be a sufficient indicator for the transition to the reaching phase, because it is possible that the climber re-sets the feet again and would stay in the preparation phase.

4.6 Error Detection

Figure 2 visualises the error detection metrics, in which d_{fk} denotes the horizontal component of the distance between foot of the supporting leg and knee, d_{hip} the distance between the hip position of the user and the reference climber, t_{hand} the reaching time of the reaching hand, d_{fw} the distance between one foot and the wall, φ_{e} the elbow angle and φ_{s} the shoulder angle.

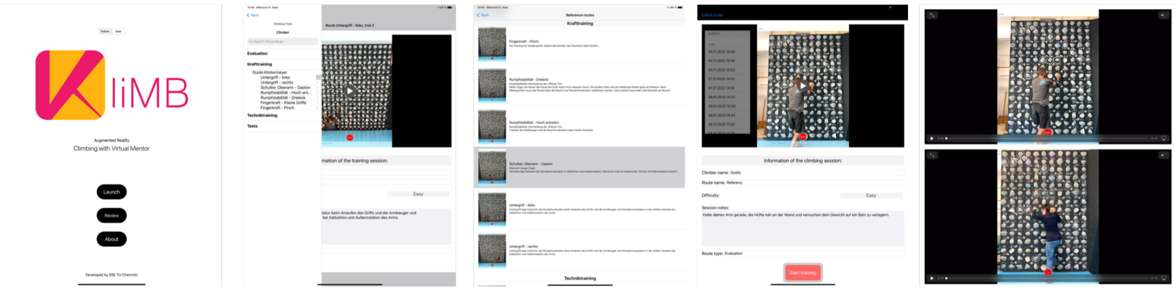
In order to analyse whether **error (a)** has occurred during the reaching phase, we check for the supporting leg, which is defined to be on the same body side as the reaching hand, whether d_{fk} exceeds a certain threshold for a certain amount of frames within this phase. If this is true, we assume that the climber has shifted the weight over the supporting leg and the error has not occurred. Otherwise we presume that the error has occurred. **Error (b)** is determined in the reaching phase by comparing the hip distance difference from the wall between the reference and current climber (user) d_{hip}, which is calculated from the z components, against a threshold. If d_{hip} is higher than the threshold, the frame is marked to have error (b). To find the reference frame that corresponds with the current user frame, a sequence alignment of the user with the reference sequence is necessary. For this alignment, we apply Dynamic Time Warping (DTW) on the vector containing the x and y components of the reference's and user's hip in wall coordinates with Euclidean distance as a distance measure. **Error (c)** is detected in the reaching phase by measuring the time t_{hand} when the reaching hand is in motion. If this time exceeds one second, the error is detected. **Error (d)** has occurred if one of the feet is detected to exceed a certain distance d_{fw} from the wall measured in z direction in the reaching phase. The **errors for shoulder relaxing (e) and decoupling (f)** show the same features but are checked in different phases, i. e. stabilisation or preparation phase respectively. For both errors, the elbow and shoulder angle φ_{e} and φ_{s} are lower than a certain threshold.

5 RESULTS

In first empirical evaluations, the system was tested by **14 probands of which the majority were beginners**. They climbed a reference route and used the developed app to obtain feedback. Currently the statistical evaluation in terms of comparison against ground truth data in form of precision-recall curves is still in progress, but the **application as well as the visual feedback** is presented here.

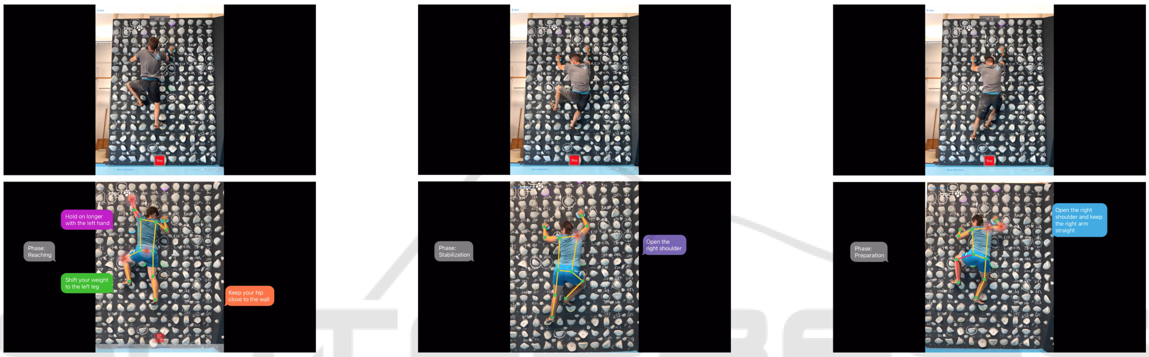
Figure 7 shows the developed feedback app. (a) In the start screen, one can select between trainer and user mode. (b) In the trainer mode, an experienced climber can record new reference routes. (c) In the user mode, the user can choose from the recorded routes. (d) When a route is selected, the user can record a new trial of his or her own and also review previous trials of this route. Before the recording starts, the setup is extrinsically calibrated. The system automatically detects when the user has put both hands on the start holds and from then on records the sequence. Moreover, the reference solution is presented as a video. (e) When the user reviews own recorded trials, he or she sees the detected errors in the own recording at the bottom and can compare against the reference at the top that is aligned by DTW.

Examples of generated feedback, i. e. for the errors occurring in the different phases, are presented in Figure 8. In a separate screen that is not presented here, the user can thereupon obtain detailed hints about what can be improved so that he or she can take this information into account for the next trial.



(a) (b) (c) (d) (e)

Figure 7: Feedback application.



(a) Errors in reaching phase. (b) Error in stabilisation phase. (c) Error in preparation phase.

Figure 8: Comparison of user (bottom video) against reference (top video) and feedback given to the user (coloured feedback bubbles). (a) User's hip position should be closer to the wall. Moreover, the user should shift the weight to the left leg and hold longer with the left hand before it reaches to the new hold. Both feet are set, so no feedback bubble appears at this point. (b) User should lower his body after having reached, so that the shoulder angle is open and the arm straight. (c) User keeps the arm bent while re-setting the feet. He or she should stretch the arm as the reference does.

6 CONCLUSIONS

This study presented an approach to detect motion errors that commonly appear with beginners in climbing scenarios. We examined skeleton extraction algorithms and found a suitable 2-D algorithm, which together with an obtained 3-D point cloud was the basis for 3-D skeleton calculation. Based on movement segmentation by analysing joint velocities, this study for the first time proposes a method that maps climbing theory into a finite state machine to represent climbing phases. By doing this, our work allows to detect errors that typically occur in those specific phases. The result is an application that provides valuable feedback to beginners. Before, such an approach has not existed.

Our next steps are the **quantitative evaluation** of the climbing motion error detection. For this, we already have labelled ground truth data and are currently collecting more data from climbers using boulder walls in various climbing halls. In terms of skeleton extraction, it is sensible to investigate **further skeleton extraction algorithms** that are continuously appearing on the market. A possible 3-D skeleton extraction solution that would also enable an implementation for Android might be the pose estimation framework MediaPipe provided by Google (Google, 2022).

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