Human Climbing and Bouldering Motion Analysis: A Survey on Sensors, Motion Capture, Analysis Algorithms, Recent Advances and Applications

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Abstract: Bouldering and climbing motion analysis are increasingly attracting interest in scientific research. Although there is a number of studies dealing with climbing motion analysis, there is no comprehensive survey that exhaustively contemplates sensor technologies, approaches for motion capture and algorithms for the analysis of climbing motions. To promote further advances in this field of research, there is an urgent need to unite available information from different perspectives, such as from a sensory, analytical and application-specific point of view. Therefore, this survey conveys a general understanding of available technologies, algorithms and open questions in the field of climbing motion analysis. The survey is not only aimed at researchers with technical background, but also addresses sports scientists and emphasises the use and advantages of vision-based approaches for climbing motion analysis.

1 INTRODUCTION

Bouldering and climbing are increasingly attracting interest across all age groups and have become trend sports all over the world.

While various studies demonstrated that climbing improves coordination, flexibility, the cardiovascular system and has positive effects on both physiological and psychical health conditions (Bernstädt et al., 2007), (Steimer and Weissert, 2017), (Luttenberger et al., 2015), (Weber, 2014), other researchers call the provided evidence into question: Due to the small number of trials they regard the evidence for the effectiveness of therapeutic climbing as limited (Buechter and Fechtelpeter, 2011), (Siegel and Fryer, 2017). As a consequence, the effects of climbing on health conditions are still unclear and there is still urgent need for further investigations, including climbing motion analysis.

From the very beginning, especially in case of competitive sports, climbing motions were analysed to assess and optimise climbing techniques. In view of therapeutic applications, climbing motion analysis has gained importance to avoid movements that are prone to cause injuries. At this point, the present survey provides a profound and exhaustive review of extant work with the focus on camera-based approaches as well as recent advances in analysis techniques, including sensors, human motion capture, analysis algorithms and applications as a highly topical knowledge base for future research.

The survey is structured as follows: Section 2 reviews sensor technologies that were used in previous work, provides an overview about available RGB-D cameras on the market and compares parameters that are relevant for motion analysis in climbing applications. This is followed by a review and discussion of motion capture approaches in Section 3 as well as algorithms for climbing motion analysis in Section 4. The findings are summarised in Section 5 and finally, an outlook at future work emphasises the potential of using latest technologies and highlights open challenges that should be addressed in future research on climbing motion analysis.

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2 SENSORS

2.1 Sensor Overview

Generally, we can distinguish between instrumented climbing walls equipped with any kind of sensors, wearables, and camera-based systems that are used for climbing motion analysis. An overview about applied sensors and the obtained sensor data is presented in Table 1. Next to the usage of only one type of sensor, there are studies that apply sensor combinations, such as (Pandurevic et al., 2018) who use both an RGB-D camera as well as force sensors.

The advantages of optical sensors compared to the other presented technologies are as follows: They work in a contact-less mode, so that the climber does not have to wear any device that could be inconvenient while climbing in terms of injuries or physical discomfort. Moreover they provide direct and comparatively accurate information about the human body: Especially RGB-D sensors allow the determination of points of interest such as the centre of mass or even the position of skeleton joints in 3-D coordinates. Besides, the adaption of the wall with installed sensor equipment can be avoided, which makes a final application more convenient for operators and users.

Since camera technology with depth sensing plays an increasingly role in recent research on motion analysis, the following section reviews latest RGB-D sensors available on the market that can be employed for climbing motion analysis.

2.2 Camera Review

The application of RGB-D cameras for climbing motion analysis involves considerations about the set-up, which includes parameters such as the distance to the wall, which is affected by the provided **range**, the camera **field of view** to capture the complete wall, the required **image resolution** of both depth and RGB image of the sensor to obtain sufficient information about the climber's body, the **depth resolution** and also the **availability of suitable skeleton extraction SDKs**. Table 2 provides an overview about current sensors with relevant parameters and information.

The comparison presented here has been made from the metrological point of view, to evaluate the convenience of using an optical sensor to track a climber on a climbing wall. Among the cameras reviewed, the Orbbec, Asus and the Intel D400 (see example point cloud in Figure 1) series show state-of-the-art features in structured light and active stereoscopy technologies, which use a triangulation process to estimate the depth and are not exposed to the multipath effect, as happens with those based on time of flight (ToF). Microsoft presents the smallest uncertainty in the depth measurement, followed by Intel. However, because the structured light technology is affected by the environmental light conditions, they are unfavourable for outdoor applications, where the ToF technology offers better results.

Figure 1: 3-D point cloud of a climbing scene captured by an Intel RealSense D435 RGB-D camera.

3 MOTION CAPTURE

The analysis of a climbing motion always encompasses motion capture and human pose estimation (HPE). In other words, analysis algorithms require input data, such as locations of defined points of interest on the body that can be tracked and analysed. In existing work, a variety of methods were used to capture human motion. The captured data ranges from a coarse body description, such as the centre of mass (CoM), to very fine-granular models, such as skeleton models describing the poses of articulated joints of a human body. Moreover, input data can be distinguished between 2-D and 3-D representations.

3.1 Centre of Mass

As already mentioned, the CoM is a very coarse description of the human body, which is analysed in several studies (Sibella et al., 2007), (Reveret et al., 2018). Even though the motion is represented by only one single point, it provides relevant information in case of climbing motions. Sibella et al. for example, analysed the trajectory of the CoM to obtain parameters, such as entropy, velocity and acceleration to draw conclusions about fluency and force of the motion (Sibella et al., 2007). They calculated the CoM as the **weighted average** of nine body segments. These body segments were obtained by detecting visual markers attached to the climber's body using cameras distributed in a calibrated volume. Reveret et al. approximated the CoM by means of a **marker attached to a harness** worn around the waist (Reveret et al., 2018). Wiehr et al. calculated the CoM from the **3-D skeleton** provided by the Kinect v2 in order to determine whether the climber reached the top of the route (Wiehr et al., 2016). Next to marker detection, the CoM can be derived from **3-D point clouds** defining a climber's body, e. g. by means of functions provided by the open-source Point Cloud Library.

3.2 Pose Estimation for Climbing Analysis

Several analysis techniques rely on a fine-granular skeleton model describing the human pose by means of several joints.

Aladdin et al. constructed an **instrumented bouldering** wall where each hold was connected to a **force torque sensor** (Aladdin and Kry, 2012). Based on the force signals and a synchronised skeleton output of a motion capture system, they were able to derive physically valid poses from several plausibility constraints and forces alone.

A very popular Czech competitive climber, Adam Ondra, "hung with sensors" to analyse what makes him such an outstanding climber (iROZHLAS, 2019). For this purpose, a **marker-based motion capture system** was used to analyse the movements and positions of his back, elbows, head and also his CoM. Next to motion analysis, the pure analysis of stature by means of his "measured" skeleton yielded that he has some advantages compared to other climbers: Next to his long neck, his comparatively slim shoulders result in less force on his fingers.

Kim et al. recognised climbing motions by **parsing a climber's body area** and the skeleton provided by the Kinect (Kim et al., 2017). This body area was determined by a foreground segmentation on a depth image. The determined body parts were then used to correct the feet and hands positions of the Kinect skeleton, which are unreliable for climbing poses.

3.3 Machine Learning-Based Pose Estimation

Next to the above described approaches to determine a human pose, extant literature brought forth various approaches using machine learning techniques to localise joint positions both in 2-D images and in 3-D coordinates. The following list provides an overview about latest and most popular image-based skeleton

Table 1: Overview: Sensors used for climbing motion analysis.

Sensor	Obtained data	Examples
Strain gauges	Sensors are attached to the holds of the wall. The obtained **forces** were used to draw conclusions about equilibrium, leg movement and body position.	(Quaine et al., 1997a), (Quaine et al., 1997b), (Quaine and Martin, 1999)
Force torque sensors	Sensors are attached to holds of a wall. **3-axis force measures** are obtained. Human body poses can be derived from the measured forces, for example.	(Aladdin and Kry, 2012), (Pandurevic et al., 2018)
Capacitive sensors	Capacitive sensors are integrated into holds. A **climber's presence** is measured by means of a change in capacitance.	(Parsons et al., 2014)
Wearables	Inertial sensors are tracking **rotation, acceleration**, and temporal information about body limbs while climbing.	(Ebert et al., 2017) , (Kosmalla et al., 2016), (Kosmalla et al., 2015)
Commercial MoCap system	A skeleton is derived from reflective markers attached on the body. Cameras with active lighting capture marker positions to derive a **human skeleton model**. The joint positions were used for the analysis.	(iROZHLAS, 2019)
Gray-scale camera	Light-emitting diodes (LEDs) were attached as markers to a climber's waist. The **position** of the LED was determined to obtain the climber's **trajectory**.	(Cordier et al., 1994a)
RGB-D camera	A skeleton extraction algorithm (OpenPose) is executed on the RGB video stream provided by the camera. Based on the skeleton, climbing technique can be analysed.	(Pandurevic et al., 2018)

Table 2: Overview about cameras available on the market.

	3-D Sensor	Principle	Range	FOV	RGB Resolution	Depth Size	Depth Resolution	Skeleton API
Orbbec	Astra S	Structured Light	0.4 m - 2 m	60°H, 49.5°V, 73°D	640×480 @30fps	640×480 @30fps	at 1 m: uncertainty≃1 mm bias≃8 mm at 2.5 m: uncertainty≃5 mm bias≃96 mm	Body Tracking SDK BodySkeletonTracker (OpenNI2)
	Astra Pro		0.6 m - 8 m		1280×720 @30fps			
	Astra (Mini)		0.6 m - 8 m		640×480 @30fps			
	Persee		0.6 m - 8 m		1280×720 @30fps			Orbbec Body Tracking (requires licence after 2018)
	TVico		0.6 m - 5 m		1280×720 @30fps			Nuitrack SDK (lic. included) Orbbec Persee SDK (lic. included)
Asus	Xtion Pro	Structured Light	0.8 m - 3.5 m	58°H, 45°V, 70°D	1280×1024	640×480 @30fps; 320×240 @60fps	Within 2 % for each distance	Gesture: 8 predefined poses Body: multiple player recognition
	Xtion Pro Live							
	Xtion 2			74°H, 52°V, 90°D	2592×1944			
Microsoft	Kinect v2	Time of Flight	0.5 m - 4.5 m	70°H, 60°V	1080×1920 @30Hz	512×424 @30Hz	at 1 m: uncertainty≃1.5 mm bias≃5 mm at 2.5 m: uncertainty≃2 mm bias≃10 mm	BodyFrame BodyIndexFrame FaceFrame
	Azure Kinect	Time of Flight	0.25 m - 2.88 m; 0.50 m - 5.46 m	RGB: 90°H, 74.3°V Depth: 120°H, 120°V	3840×2160 (16:9); 4096×3072 (4:3) *12MP, rolling shutter*	1024×1024 @5-15fps; 640×576 @5-30fps *1MP, wide and narrow views individually*	15 % to 95 % reflectivity random error std. dev. ≤ 17 mm typical error < 11 mm + 0.1 % of distance	Body Tracking SDK Cognitive Services: Face
Intel RealSense	D415	Structured Light	0.16m - 10m	RGB: 69.4°H, 42.5°V, 77°D (±3°) Depth: 65°H, 40°V, 72°D (±2°)	1920×1080 @30Hz *rolling shutter*	1280×720 @30fps; 848×480 @60fps	at 1m: uncertainty≃1.5 mm bias≃2 mm at 2.5 m: uncertainty≃15mm bias≃25 mm	Nuitrack SDK
	D435		0.20 m - 10 m	RGB: 69.4°H, 42.5°V, 77°D (±3°) Depth: 87°H, 58°V, 95°D (±3°)	1920×1080 @30Hz *global shutter*			
	LIPSedge DL	Time of Flight	0.2 m - 1.2 m; 1.0 m - 4.0 m	RGB: 74.2°H, 58.1°V, 88°D Depth: 74.1°H, 57.5°V, 92°D	1920×1080 @30fps	320×240 @30fps	Up to 0.5% of distance	LIPS Software

detection methods. More information can be obtained from the provided references:

- ConvNet (Marín et al., 2018)
- Nuitrack (Nuitrack, 2019)
- OpenPose (Cao et al., 2018), (OpenPose, 2019)
- ITOP (Haque et al., 2016), (ITOP, 2019)
- UBC3V (Shafaei and Little, 2016), (UBC3V, 2019)
- Microsoft HPE (Xiao et al., 2018), (Microsoft HPE, 2019)
- 3D Human Pose Estimation in RGBD Images for Robotic Task Learning (Zimmermann et al., 2018), (RGB-D pose 3-D, 2019)

The problem of machine-learning-based HPE for climbing poses does not have profuse research so far. Difficulties can be seen in finding **specific datasets of climbing poses**, since the available open datasets are optimised to detect humans in upright frontal poses. Vähämäki et al. presented a HPE method for climbing that uses a set of computer-generated synthetic data to train the model (Vähämäki, 2016). The dataset was generated by building a rendering pipeline that produces a 3-D mesh of a virtual climber and renders depth images from typical camera angles. Ground truth joint positions and poses of body parts were generated in an indoor climbing scenario. The classification algorithm uses a random decision forest to estimate skeletal joints directly from depth images. The research achieved good results in synthetic data, making a reasonable generalisation of real-world data. Although the training data does not capture all the variations observed in real scenarios, for which much more information with human annotations is required, the proposed method is a valid reference to enrich datasets related to sport climbing. Unfortunately, Vähämäki et al. provide neither data for training nor the resulting model.

3.4 Conclusions

The estimation of position and orientation of the human body limbs from individual images or video sequences has been studied in 2-D and 3-D spaces, by detecting the joints of the body using RGB and RGB-D images. Although, as Marín et al. indicate, a great effort has been put to solve the problem, it is still far from being solved (Marín et al., 2018). Beyond dealing with the **high degrees of freedom** of the human body, there are more challenges offered by the **clothing, camera views and self-occlusions**. In this sense, climbing is even more challenging to pose estimation algorithms than other activities performed in an upright pose, due to the position the climber adopts is non-conventional and requires the construction of **specialised datasets** to train successful models.

With the popularisation of 3-D cameras and the increasing precision they offer, more and more research is being carried out with these types of sensors to determine and measure a climber's pose. The results show that techniques based on optical sensors are promising, although much **computing power** is still required to offer results in **real-time**.

4 ALGORITHMS FOR MOTION ANALYSIS

While climbing behaviour has been a matter of interest in recent years motivated by the popularisation of bouldering and its inclusion in sport competitions, early studies such as (Cordier et al., 1994b) are still a benchmark to carry out new research. The experiment in that study was conducted using a **light-emitting diode connected to the climber at waist level**, and a set of aligned photographic cameras. The trajectory of the light drew the climber's route on a plane; the ratio between the length of such trajectory and the convex hull that enclosed it, defined the **entropy** of the climber's route. As a result, Cordier et al. demonstrated the inverse relationship between the experience of the climber and the entropy of a climbed route.

Mermier et al. contributed to the formulation of an appropriate model for sport climbing behaviour by introducing new parameters to measure climbing athletes and by proposing the use of **Principal Component Analysis (PCA)** to treat the parameters as uncorrelated variables (Mermier et al., 2000). They demonstrated that a climber's performance is more susceptible to trainable variables such as strength, endurance, and flexibility than physical attributes such as height, arm length, and body weight.

Following the work of Cordier et al. (1994), Sibella et al. carried out measurements in groups of recreational climbers using a **MoCap system with passive sensors** (Sibella et al., 2007). The aim was to compare climbing strategies based on the route described by the climber's CoM. They improved the prior technique introducing the register of the CoM in a 3-D space, being able to measure the **entropy, velocity and acceleration** in the frontal, sagittal and transverse planes of the climbing space. They defined **fluency** as "the effectiveness of the movement" measured by means of the entropy of the climbing route, as well as the concept of **agility**, as a combination of the speed and acceleration of the CoM.

Pandurevic et al. added quantitative methods of force and endurance evaluation employing a wireless **instrumented climbing wall**, in conjunction with a **3-D camera** (Pandurevic et al., 2018). They measured the 3-axis force applied on the holds by hands and feet, and determined the route of the centre of gravity using OpenPose to construct a climber's skeletal model. The system allowed measuring the **position and climber's force** within an energy budget in a wireless way with the possibility of analysing the pose of the climber's limbs through a skeletal model.

Analysis of the speed has been carried out by Reveret et al. In their study, they worked with high-level climbers using an international accredited wall, utilised to validate records, and attached a **motion sensor** to the hip of the climber (Reveret et al., 2018). They identified **dynos**, which are dynamic moves, as a relation between vertical and absolute velocities of the hip.

4.1 Motion Planning

Motion planning includes the prediction and simulation of climbing motion behaviour to plan or create new climbing problems and to obtain a set of anatomically possible movements that can be proposed to a climber for his or her next move.

Among the first studies, Ouchiet al. created a model for the **prediction of climbing behaviour** based on a data-driven analysis of a group of children climbing a prepared wall with a series of uniform holds with embedded sensors (Ouchi et al., 2010). Pfeil et al. proposed a system to guide the design of routes by **simulating climbing behaviour**, inspired by the background software used to run physical simulations in the designing of climbing clothes and equipment (Pfeil et al., 2011). They developed a tool that enables experienced and novice climbers to design quality routes by placing holds in a virtual climbing wall, that later is probed by a simulated virtual climber.

Naderi et al. addressed the problem of **offline route planning** for wall climbing by simulating bouldering with a graph-based application, optimised through a k-shortest path finding algorithm (Naderi et al., 2017). Their solution proposes alternative paths depending on the anatomic characteristic of the climber, e. g. strength, flexibility, or reach. In contrast to previous works, they contemplated limbs hang free for balancing and the use of the wall friction. Additionally, the simulated agent can move more than one limb at a time, restricted to use at least two holds simultaneously. The simulations showed plausible solutions on short bouldering routes.

Augmented Reality (AR) enabled users to **create climbing routes** for the bouldering board MoonBoard with their smart phone. The MoonBoard is a special climbing wall that has a standardised layout and hold sets, whereas each hold is equipped with an LED to show a configured route (Daiber et al., 2013a). Next to AR, Virtual Reality (VR) makes it possible to **share the experiences** professional climbers made on extreme routes allowing other climbers to experience these demanding routes as well, at least virtually (Adidas, 2019).

4.2 Teaching and Training

Teaching bouldering requires multiple demonstrations of postures and movements a novice climber must imitate. Cha et al. analysed the movement of limbs from a biomechanics point of view, employing two Microsoft Kinect V2 cameras to construct realistic 3-D **animations that can be followed by the novice climbers in a computer monitor** (Cha et al., 2015). For the simulation, the study divided into phases the movements to change from one initial posture to another finished one, loading individually the velocity of hip, forearms, upper-arms, thighs and shins. The joint flexion angles were estimated also within each phase. Difficulties in the detection of limbs when they are close to the wall were pointed out, which required the use of an acrylic transparent wall specially made for this study. The research presented acceptable results for beginners training, but deficiencies were observed working with faster and more experienced climbers, due to problems related to the correct reproduction of realistic speeds and angles in the animations.

Kosmalla et al. presented a system for visualising reference motions on a bouldering wall (Kosmalla et al., 2017a). They addressed the difficulty to teach and learn simultaneously because it is hard to remember all the movements exactly while ascending. To solve this, they proposed to present an augmented real-time **video projected on the wall** while the climber performs the training. There is a variety of further publications examining the application of **augmented or mixed reality** for teaching purposes in climbing, such as (Wiehr et al., 2016), (Kajastila and Hämäläinen, 2014), (Kajastila et al., 2016), (Daiber et al., 2013b), (Kosmalla et al., 2017b).

4.3 Conclusions

Due to the unavailability of reliable skeleton data, the majority of motion analysis approaches relied on body representations, such as the hip centre or the

CoM, or on combinations of existing HPE algorithms and external sensors such as body-worn motion sensors or force sensors integrated into the wall. Measured **parameters** focus on entropy, velocity, acceleration and the distance to the wall to draw conclusions about fluency, agility, force, energy and the detection of dynos. Other approaches are related to **teaching** and the simulation of climbing behaviour for **climbing prediction** and route creation.

5 SUMMARY AND OUTLOOK

Taken together, real-time marker-less, vision-based **motion capture for climbing motions** is far from being solved and requires further research activities. The availability of joint positions would be a great benefit for a more **detailed and precise climbing analysis**. So far, there are still open questions related to a **comparison** of a novice's climbing style with the technique of an experienced climber to provide feedback for an effective climbing. Moreover, neither of the available studies was dedicated to the detection of **typical motion errors** in terms of technique. Future climbing applications could work completely by means of a camera and without additional information, such as marker positions or wearable sensors. The applicability in the improvement of teaching, the analysis of athletic performance and the contributions to the health sector and the entertainment industry suggest an even greater growth in bouldering research.

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