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Master Thesis

ClimbSense
Automatic climbing route recognition using wrist-worn inertia measurement units

Felix Kosmalla

`felix.kosmalla@dfki.de`

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Supervisors:	Prof. Dr. Antonio Krüger
	Dr. Cassim Ladha
Advisor:	Florian Daiber

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Reading Hints

- While the following examples, arguments, and descriptions apply equally to both genders, for the sake of ease of reading, only the female pronouns are used in this thesis.
- All URLs have been last accessed on August 10th, 2014.

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Abstract

Today, sports and activity trackers are ubiquitous. Runners and cyclists especially have a variety of possibilities to record and analyze their workouts. In contrast, the sport of climbing did not find much attention in consumer electronics. Until now, the recording of climbed routes during a climbing session is only possible with pen and paper or low fidelity smartphone apps. If climbing data were available in the same quantified manner like cycled or ran distances, several applications would be possible. These range from simple training diaries to virtual climbing coaches or usage analytics for a climbing gym operator.

In this thesis, a preliminary user study with 92 climbers was conducted that shows that an automatic route recognition system would enable climbers to track routes without the need for a smartphone, pen and paper or any interaction at all. A system is proposed that automatically recognizes climbed routes using wrist-worn inertia measurement units (IMUs). This is achieved by extracting features of a recorded ascent which are later used as training data for the recognition system. To verify the recognition system, cross-validation methods were applied to a set of ascent recordings that were assessed during a user study in a local climbing gym. The evaluation resulted in a high recognition rate, thus proving that an automatic route recognition using wrist-worn IMUs is possible and operational.

Contents

Lists

Figures

Tables

1. Introduction

The tracking of sports activities like running and cycling with smartphones and special sport devices is becoming increasingly popular [19]. However, climbing did not find much attention in sports tracking from a Human-Computer Interaction (HCI) point of view. Currently, it is only possible to assess the progress of one's climbing training by hand. Common methods are noting the climbed routes and their difficulty levels in a book, spreadsheet, or with the help of low fidelity smartphone apps. All investigated methods for climbing tracking lack user-friendliness and additional value. In this thesis, a system is introduced which is able to record and automatically recognize the route that a user is climbing.

1.1. The Quantified Self Climber

The Quantified Self movement describes itself as "international collaboration of users and makers of self-tracking tools"[1]. Members of this movement track their daily activities such as walked distance, food intake, but also biometric measurements like blood pressure, heart rate, and the body fat. A similar, but less extensive form of these practices can be found in the usage of activity trackers like the fitbit[2] or the Nike+ Fuel Band[3]. These trackers are able to log the wearer's activity, e.g. steps made during a day or the recording of sleep cycles.

The following scenario shows that the data acquired with the help of Quantified Self methods could be used for several other analyses and concepts that do not necessarily follow the original motivation behind this movement. While the acquisition of climbing data is not only beneficial for the climber herself, it is also of commercial interest by the climbing gym operators. An automatic route recognition and tracking system, as it is described in this thesis, could be the first step for such applications.

> When Paul enters the climbing gym, his phone notifies him that, according to his training plan, today is a cardio day. Since Paul uses his sensor armbands that automatically record every route he climbs, the system adapts to him. It knows that Paul usually climbs in the grades around VII+ and likes overhanging routes with big holds. Thanks to crowd sourced information every route is tagged with information about

[1] `http://quantifiedself.com/about/`
[2] `http://www.fitbit.com`
[3] `http://goo.gl/Hi7Y6`

the holds, if dynamic moves are required or which inclination the wall has.

The system suggests a cardio training, which requires Paul to climb five different routes with three repetitions, within 30 minutes. To make things easier, five routes are proposed which are one level easier as Paul's average climbing skill. Paul's climbing partner Sarah, who also uses the system, is doing cardio training, too. Since Sarah is used to climb harder routes, she gets other route recommendations, which are close to the current route Paul is climbing. The smartphone application shows an overview of the already climbed routes and guides both climbers through the climbing hall.

After an exhausting training session, Paul and Sarah sit in the lounge and compare each other's training progress on their smartphones. The system summarizes the last month's sessions and visualizes the training progress. Besides an evaluation of what they climbed, the system also assesses the climbing performance. The system can analyze how much control the climber has or how fast she is moving. Based on the past climbing history the system creates a training plan. A common technique to increase the climbing performance is to climb routes that require moves or holds which are unpleasant for the climber. The day after tomorrow is scheduled as technique day. For this, the system selects a number of routes, which have a higher difficulty level then the routes Paul and Sarah climbed in the last weeks.

Back in the climbing gym office, Michael, the manager of the gym opens the dashboard of the climbing gym management software. The dashboard displays operating numbers like the number of routes, the average route age, and the route distribution. Thanks to the climbing history data he automatically receives from his customers, he can compare the present difficulty distribution with the skill levels of his customers. He sees that many new customers started climbing which require routes in the easier difficulty levels. To counterbalance, he schedules ten new routes for beginners that should be created during the next route setting session.

Michael notices a warning icon. The system detected that a route that is usually climbed very often has lost a lot of traffic. When checking the situation Michael realizes that a new route passes straight through the older route. Since the older route was set a couple of month ago he decides to replace it with a new one located in a different sector of the climbing gym.

1.2. Benefits of Quantified Self in Climbing

As it can be seen in the scenario, the assessment of climbing performance data, as it is already common for sports like running or cycling, is beneficial for the climber herself and also for the climbing gym operator. When a system is able to automatically recognize different aspects of a climbing session, it is possible to use the data for different user groups. The climber gets a detailed evaluation of her training progress. Her virtual climbing trainer knows how she climbs and can adjust her training plan according to her climbing habits and progress. Also a climber who is not that interested in a performance gain can benefit from such a system. She could use it as route browser, finding routes that fit her current mood the best. The system could also give recommendations like "your friend climbed *Blue Frog*, you should try it". These recommendations are based on the usual climbing habits and the climbing habits of the user's friends.

Finally, climbing gym operators profit by the data which they automatically receive from their customers. They can adjust the route setup of their climbing gym to increase the utilization of the gym. The adjustment is based on the knowledge of the difficulty distribution of the currently set routes and the distribution of the climbing skills of the customers. This data is automatically inferred from the anonymized usage data, obtained from the customer's climbing history. Statistics of single route usage can give insights in the quality of currently set routes. Routes with a small usage can be replaced by new, more appropriate routes. As a result, not only the climbing gym operators profit by serving more customers, but the climber also gets access to a larger selection of quality routes.

The tracking of routes by the climber could be done with the help of pen and paper or a smartphone application. Pen and paper have the disadvantage that the user would have to transfer the collected data in e.g. a spreadsheet to analyse her progress in a semi automatic way. Furthermore, carrying a pen in one's pocket may lead to severe injuries during a fall. Using a smartphone in a climbing gym has also several disadvantages. On the one hand the user simply has to carry it around. Putting the phone in her pocket could, depending on the size of the phone, result in a restricted mobility. As in the example of the pen, the user could hurt herself on the phone when falling, maybe even breaking the phone. The usage of chalk, a white powder that is used to dry the climbers fingers before and during an ascent, may result in a dirty phone. Independent from the device or method specific disadvantage, the user would still have to somehow track her ascents manually. A preliminary user study showed that some users do not want to use a smartphone to track routes during a climbing session (see Chapter 3). Most of the users stated that they want to focus rather on climbing, although they may be interested in the resulting data.

As described above, there is currently no optimal method for tracking the routes a climber is performing throughout a climbing session. The possibilities which would arise when being able to automatically assess the climbed routes are various. They range from statistics over virtual climbing coaches to usage statistics of climbing routes that could be used by gym operators. This motivates the development of a lightweight system for route tracking which a) does not hinder her movements during a climb and b) does not require any user interaction, would solve this problem. In the following the concept and implementation of such a system is described.

1.3. Outline

The thesis is structured as follows: This chapter is followed by *Foundations* which gives an introduction into Quantified Self, a movement which is dedicated to track one's own life. The *Quantified-Selfers* use sensors that record biometric data like heart rate, glucose level or skin conductivity. Spreadsheets or specially developed applications are used to track one's alcohol consumption. The chapter also shows parallels to already available customer ready tracking devices. These devices can track sports, activities and even the sleep cycle of the wearer. This is followed by an introduction in several sport tracking topics, including sensor based assessment of swimming velocity or the skill assessment of a golf putt. Afterwards, climbing in its various forms is described. Climbing did not find much attention in HCI research. The few relevant climbing related research topics are introduced in Chapter 2.

This includes work to technology aided route creation, instrumented climbing walls, and automated skill assessment. Finally *ClimbAX* [21], a system for automatic climbing skill assessment is discussed in more detail, since it is very close to the work presented in this thesis. Ladha et al. developed wrist worn sensors which allow an assessment of power, control, stability, and speed. They used this data in a study to predict the score of participants in a climbing competition.

Followed by the foundations, the aim, method, and results of a preliminary user study is introduced. The aim of the study was to get an initial insight into tracking habits of climbers. For this, 92 climbers were recruited over several Facebook groups. They were asked to complete a small survey which contained questions about their climbing habits, their sport tracking methods, and how they currently record their climbing progress. Based on the participant's feedback about tracking of routes in a climbing gym, requirements for an automatic route tracking system are defined.

The chapter *Automatic Climb Recognition* explains the concept and functionality of the proposed route recognition system. To automatically track routes, the climber has to wear inertia measurement units (IMUs) which are attached to her wrists. These devices record the movements of the climber during an ascent and recognize whenever the climber grips a hold. Whenever a hand rests on a hold the system extracts the user's arm orientations. These sequences of orientations are used to characterize a route. Multiple recordings for a single route are used as training sets. New recordings are compared with the training data and are matched to the available routes. As a result, the system can detect which route the user was climbing.

An evaluation of the implementation shows that the system is functional. In a user study eight participants were asked to climb 5 different routes in a local climbing gym. The difficulty of the routes ranged from IV- to VI+ and varied in shape and type. To evaluate the performance of the system, different cross-validation methods were applied. A two-fold cross validation resulted in a recognition rate of 93.92%. Finally, possible improvements of the recognition are discussed.

The final chapter concludes the findings of this thesis and discusses future work.

2. Foundations

2.1. Introduction

2.2. Quantified Self

Keeping track of one's health and fitness is not only interesting for top athletes. One of the first researches who dedicated himself to the recording of his everyday live and his biometric data was Steve Mann. He presented the *Underwearable Computer*, a collection of a respiration sensor, ECG, EEG, and a skin conductivity sensor[23]. The sensor readings were displayed in realtime on a miniature eyeglass-mounted screen (see Figure 2.1).

In May 2011, the first international conference for quantified self took place in Mountain View, California. The quantified self movement describes itself as an "international collaboration of users and makers of self-tracking tools"[1]. Choe et al. state that "Collection and quantifying data is just one aspect of quantified self. The ultimate goal is to reflect upon one's data, extract meaningful insights, and make positive changes, which are the hardest part of QS."[4] This goal is achieved by collecting data from the daily life by means of personal tracking devices like pedometers, GPS loggers, wearable sensors, as well as through manual logging, for example noting down one's mood or food intake.

In their work [4] Choe et al. investigated why and how Quantified-Selfers collected data about themselves. For this, they analysed 83 video posts on the quantified self blog. They classified the found motivations into three categories: 1) to improve health, 2) to improve other aspects of life and 3) to find new life experiences.

For health improvement, data like the blood glucose level, body weight, exercises, muscle mass, body fat, food intake, and sleep cycles where logged. The data was used to cure or manage a condition, achieve certain fitness goals, identify relationships, and help to make better health decisions. To improve other aspects of life, for example to maximize work performance, time tracking was applied to find new ways to be more efficient. A participant stated that she would take a picture everyday for a year to capture each day's state of mind. To satisfy curiosity and having fun, the frequency of "puns" was logged, to see how often these puns happened and what triggered them. Another participant tracked every street that she was walking in Manhattan which should explore as much of the city as possible.

[1] `http://quantifiedself.com/about/`

Figure 2.1.: WearComp by Steve Mann. His wearable computer included a collection of a respiration sensor, ECG, EEG, and a skin conductivity sensor [23]. Reprinted from Glogger - Own work. Licensed under CC BY-SA 3.0, retrieved via `http://commons.wikimedia.org/wiki/File:QuantimetricSelfSensingPrototypeMann1996inset.jpg`

Figure 2.2.: Baby Lucent. The system which aims at first time parents consists of a smart pacifier, a smart feeding bottle and a smartphone application [14].

The techniques used for data logging ranged from accelerometer driven activity trackers like the fitbit[2], over WiFi enabled scales to manual tracking in spreadsheets or in Google Docs. Common pitfalls in data logging were to track too many things which resulted in a *tracking fatigue*. To overcome this issue one participant stated "If you can't automate your tracking, make it binary". An example for this would be to count the number of times one drinks alcohol, instead of tracking which type and which amount. Another common failure was not to track triggers and context. As an example one participant only tracked her weight but not what she was eating.

Quantified self is not only limited to adults. Gaunt et al. proposed a concept for an infant monitoring solution [14]. The system aimes at first time parents and provides a smart pacifier, which analysis bacteria level and the temperature of salvia, a smart feeding bottle, which measures the infants food intake and analyses it's nutrition content, and a smartphone application which acts as the primary interface and suggests optimal feeding time (see Figure 2.2). According to Gaunt et al., most of the participants stated that the product would be inherently useful. Later on this positive attitude changed in more critical thinking, since one would "trust the app too much and not your instincts" [14].

Collecting biometric data as in the examples above does not necessarily require the user to evaluate the data on her own. Curmi et al. stated that "most existing [tracking] tools for sharing biometric data lock researchers into vendor-specific solutions that cannot be easily adapted to the specific researchers' requirements, users' needs and ethical considerations". To overcome this issue, they developed an open source system to share real-time biometric data over social networks. Some of the

[2] http://www.fitbit.com

core requirements for the system were real-time sharing of biometric data, the possibility to send real-time feedback like cheering, and the logging of user interactions. Researchers were able to use one or all of the above features.

Similar commercial systems already exist, which either provide health data to the users' care provider or to the general public via a unified API. *Ginger.io*[3] provides a smartphone application for the enduser that tracks active and passive data. Active data is self-reported and includes information about the general condition and the users' treatment plan. Passive data assess interaction data: how many calls, for how long, to how many people, at what times. Location data is also automatically tracked, which includes how far the user travels per day and how much the user walks and bikes. The data is collected and evaluated before providing it to the user's care provider. In the case of *humanapi.co*[4] the user can still use her own tracking devices or smartphone applications. Later on, the generated data are uploaded into the online portal. The system unifies the data and provides API endpoints to, for example blood pressure, body fat, locations, or meals.

Although Quantified Self as described in the beginning of this section seems to be a subculture, there are also consumer ready devices which share a common subset with the Quantified-Selfers' attitude. While quantified-selfers tend to continuously track one or more facets of their live, ordinary users usually restrict tracking to some sorts of activity, e.g. sports [31]. The following chapter introduces consumer ready tracking devices and shows how people use them to enhance their daily live and even as social communication tool.

2.3. Activity Tracking for the Consumer

As mentioned above, patterns of Quantified Self cannot only be found in the same-named movement, but also in todays' consumer electronics. There are a number of devices and smartphone apps available which enable the user to track various parts of her live. This ranges from sports tracking, through activity tracking, to sleep cycle logging. Examples for devices to track sports activities are sport watches like a Garmin Forerunner[5], which can be used for cycling, running, and even swimming, or simpler GPS enabled devices. Golfers can use special sport watches[6] that incorporate a course view and a built-in swing metric.

Not only sports can be tracked, but also daily activities. For this, activity trackers like the fitbit, the Nike+ Fuel Band[7] or the Jawbone Up[8], can be used (see Figure 2.3). Some of these trackers log the steps a user is walking during a day, records sleep cycles, and calculates the number of calories burned. WiFi scales log the users' weight loss over time and help to keep track of the progress. Many of the

[3] `http://ginger.io`
[4] `http://humanapi.co`
[5] `http://goo.gl/iVRLCV`
[6] `http://www.garmin.com/en-US/golf/`
[7] `http://goo.gl/Hi7Y6`
[8] `https://jawbone.com/up`

Figure 2.3.: Activity trackers. From left to right: Nike+ Fuel Band with application, Fitbit Flex, Jawbone UP, Garmin Vivofit [26, 10, 16, 12]
.

devices named above incorporate a corresponding smartphone app that visualize the recorded data, rewards the user with achievements, acts like a mobile coach, or makes it possible to share data within social networks. Smartwatches like the LG G Watch[9] are getting more and more popular. Using the included sensors, activity tracking could be performed by the smartwatch itself.

2.3.1. Motivation for Tracking

The motivation behind activity tracking has been researched by Rooksby et al. [31]. They conducted an unstructured interview with 22 participants and could identify fives styles of personal tracking:

- **Directive Tracking.** Quantified Self methods are used to reach a goal, e.g. a certain daily calorie burn, or specific number of steps per week.
- **Documentary Tracking.** Users are interested in documenting their activities, rather than changing them. As an example, a participant who worked in a shop stated that she used her pedometer to log how far she was moving despite being inside a building.
- **Diagnostic Tracking.** The intention behind diagnostic tracking is to find the cause of an effect. A participant used her Jawbone UP to track her sleep cycles to find out why she is tired in the morning.
- **Collecting Rewards.** The gamification methods used by some devices motivates the users (e.g earning an achievement when doing 10.000 steps a day).
- **Fetishised Tracking.** Some participant stated that they used the device exclusively out of interest in gadgets and technology.

[9] `http://www.lg.com/us/cell-phone-accessories/lg-W100-g-watch`

Sharing also plays a big role for the motivation of the users. Ojala & Saarela investigated the social needs and motivations to share data in online sports communities [27]. They conducted a user interview study with 20 participants that used three different online portals for sharing of personal training data (Suunto Movescount, Nokia Sports Tracker, Polar Personal Trainer). Ojala & Saarela identified seven main categories that motivated them to use the online communities. Three of them were 1) social interactions, 2) interesting content, and 3) peer and community support. Social interactions as “like” or “thumbs up” functions and commenting on actions of others was experienced as highly motivating. Another highly appreciated feature was the ability to see what their friends are doing. The third category includes the motivation which arises through seeing other peoples’ activities and the resulting social pressure. Conversely, the reputation and the possibility to compare one’s own progress with the others motivated the participants to upload their training data.

2.4. Tracking Technology

While the previous section described consumer ready devices and applications, the following section introduces research topics that laid the foundation for them.

Kranz et al. evaluated *GymSkill*, a personal trainer for a balance board [24, 19]. *GymSkill* is a smartphone application which assesses the exercises performed on a balance board. This was achieved by placing the smartphone on the balance board which could then recognize the exercises with the help of the built in accelerometer sensors. Using *Principal Component Breakdown Analysis* (*PCBA*) they could assess the smoothness and continuity of movement, the global motion quality, and the usage of the board’s degrees of freedom. They evaluated the assessment algorithm itself with the assessment of a professional coach as ground truth, which showed good results. Furthermore, qualitative user feedback showed that the application could reach a training goal and that it would motivate to regular training.

Swimming as a sport got also attention from some researchers. Daukantas et al. made a first step in measuring swimmer performance with inertial sensors [9]. They chose the swimming style *butterfly stroke*. Daukantas et al. used an accelerometer sensor that was attached to the swimmers spine. In their work, they stated that several problems arise when trying to assess the moving speed from acceleration data. One problem would be that the acceleration is two term superposition. The signal consists of the acceleration that arises through movement and also the gravitation of the earth. To overcome this issue, the stroke rate in combination with the knowledge of the pool length is used to assess the speed of the swimmer. Furthermore, useful information such as the number of strokes per lap, instantaneous stroke rates and durations of various swimming process intervals could be assesses based on the accelerometer readings.

Stamm et al. also tried to measure the swimming velocity with the help of an accelerometer that was attached the to swimmers sacrum [33, 32]. The collected data was segmented into different phases (*push off, glide, strokes, and start/stop times*). Theses phases were then used to calculate the velocity by integrating the total acceleration. This velocity was normalized using the lap time derived by the start and stop points. An evaluation showed that “the direct comparison between the accelerometer-quantified velocity profile and the SP5000 [a tethered speed probe] velocity profile indicates a good match”.

Kooyman et al. presented a gyroscope driven system to improve motor skills while performing a golf putt [18]. With the help of the gyroscope, it was possible to identify the several phases (backswing, downswing, contact, and follow through) of the put. The putting tempo is defined by the ratio of backswing:downswing. Ideally this ratio is 2:1. The assessed tempo in combination with a video recording was given as feedback to the user. A user study showed that experienced and unexperienced participants improved their putting performance after using the feedback GUI.

Morris et al. introduced *RecoFit*, a system for automatic tracking of repetitive exercises [25]. They used an arm worn Inertia Measurement Unit to recognize exercises performed in a gym. Main features of their system were 1) the segmentation of the sensor data in workout and non-workout readings, 2) the recognition of the exercise itself, and 3) counting of the repetitions. They used a *Support Vector Machine* (*SVM*) that was trained with five seconds windows of different features. For the recognition of the exercise type itself, multiple SVMs were used. Twenty participants were recruited for an evaluation study. Each participant had to to perform two rounds of a four-exercise course. The evaluation resulted in average recognition accuracy of 99.3%

2.5. Climbing and HCI

Climbing in its many forms did not get as much attention in terms of tracking, skill assessment, or technology enhancements as much as other sports. Before going into detail of previous climbing related research in Human Computer Interaction, the following section introduces in the various climbing forms.

2.5.1. Introduction to Climbing

Sport climbing can be performed indoors as well as outdoors. Indoor climbing gyms provide the climber with a variety of routes in different difficulty levels. Artificial holds are mounted to the climbing walls which allows the route setter to vary in difficulty. A climber can decide whether she wants to climb *top rope* or *lead*. In the first case, the climber is tied on a rope that leads from the bottom to the top, passing through carabiners and is held fast by a second person, the belayer, with the help of a friction device. In case of a fall the belayer prevents the climber from hitting the ground. *Lead climbing* describes the type of sport climbing where the rope is carried up by the climber who has to clip the rope into carabiners, which are also called quick draws. In contrast to climbing gyms, where artificial holds in different shapes are mounted on the climbing walls, climbing outdoors requires the climber to find suitable holds on the rock by herself. Often it is not possible to place a top rope in outdoor crags, which makes it necessary to do a lead climb. Depending on the location, there are bolts, pre-placed into the rock, or the climber faces the bare wall. These crags require the climber to place the protection devices like nuts and friends by herself.

Another discipline which requires neither a rope nor a harness is bouldering. Bouldering is climbing in low heights that is performed indoors as well as outdoors. Special bouldering gyms imitate isolated boulders, like those that can be found in the forests of Fontainebleau, Paris. Artificial climbing walls are surrounded by thick mats that prevent a climber from injuries in case of a fall. When bouldering is performed outdoors, a portable crash pad is used which is placed under the climber (see Figure 2.4).

Figure 2.4.: Outdoor bouldering. To prevent injuries, a crash pad is used when bouldering outdoors.

Figure 2.5.: BouldAR. Using augmented reality, routes could be defined by placing virtual markers over the camera image.

2.5.2. Climbing in HCI Research

The following section introduces in different types of climbing related research. This includes work to technology aided route creation, instrumented climbing walls, and automated skill assessment.

In case of climbing gyms, experienced climbers are in charge of setting routes. It requires an amplitude experience to set routes that have a good balance between difficulty, trickiness, and an enjoyable ascent. Pfeil et al. propose a climbing route designer that aims to enable even unexperienced climbers to create quality routes [29]. Their system enables the user to place holds on a virtual climbing wall, which is later on climbed by a simulated virtual climber. An informal user study showed some limitations that arised because of missing implementation of certain climbing moves like jumps, dangling feeds, using the wall where there are no holds, and feedback on why a move fails. They concluded that this system could be used by experienced and novice climbers to design routes for children. Daiber et al. created an augmented reality smartphone application which enabled the user to create routes on a special bouldering board (Moonboard[10]). For this, the user had to touch the camera image of the climbing wall to place an augmented marker above the hold on the corresponding position (see Figure 2.5). Since the system was able to detect the different standardized setup of the board, routes could be created and shared with other climbers in climbing gyms that used the same board.

[10] http://www.moonclimbing.com/moonboard/

Figure 2.6.: Digiwall. An instrumented climbing wall [22].

There are various possibilities to sense a climber on the climbing wall. This can be done either with body worn sensors, image processing, or, as in the case of the following papers, via instrumented climbing walls (see Figure 2.6). Liljedahl et al. proposed *Digiwall*, which uses holds with built in capacitive sensors and LED's [22]. With the help of this augmented climbing holds,*Digiwall* can sense the climbers position. This allows for different games, competitions, and challenges. One example is the "Collect Holds" mode. In this mode, the user is required to collect as many illuminated holds in 60 seconds as possible. For this the user has to climb to the illuminated hold and touch it. A playback of the sound should reward and motivate the user.

A very similar instrumentation was done by Ouchi et al., whereas the goal of their work was to model play behaviour of children [28]. The used climbing holds incorporated a LED and a strain gauge. Their work should help to design age-appropriate and safer playground equipment.

Aladdin & Kry used an instrumented climbing wall for static pose reconstruction [1]. The holds incorporated 6-axis force torque sensor. This sensor enabled the reconstruction of the climber's pose during an ascent . An evaluation showed that dynamic motions and higher errors coincide. They concluded that their system could be used, in combination with projectors, for rehabilitation purposes.

The work of Fuss & Niegl also used torque sensors to measure the performance of a climber [11]. They collected data on three climbing events. An instrumented climbing hold with two 3D force transducers was mounted on a specific route (see Figure 2.7). The collected data was segmented into the three phases of contact: *set-up phase*, *crank phase*, and *lock off*. While the first phase describes the initial contact and optimal positioning of the hand on the hold, the second phase incorporates the

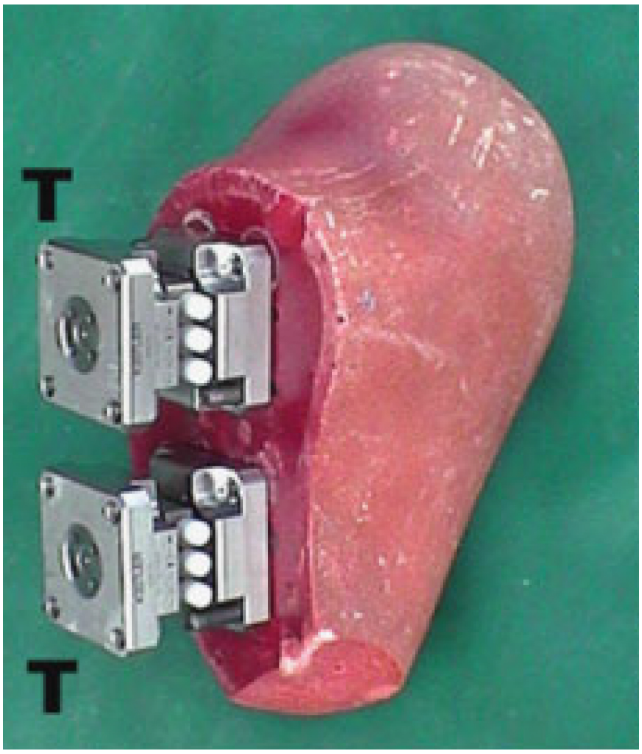


Figure 2.7.: Instrumented climbing hold. Fuss & Niegl used an instrumented climbing hold with two 3d force transducers to measure the performance of a climber.

gripping itself. The last phase describes the transfer of load to other limbs. With the help of the collected data, the performance of a climber could be assessed.

Kajastila & Hämäläinen introduced a system that augmented a climbing wall with the help of a projector and a depth camera [17]. In their work they conducted a preliminary Wizard of Oz study with six interaction prototypes. One example was *route building*: by simply climbing, all holds that are used create a new route. *Hand marks* enable a trainer or simply another climber to define the holds the current climber has to use. This was done by clicking on the holds on a screen with a mouse. The *Route automator* projected an endlessly progressing route for endurance training. A concluding structured interview showed that "the augmented climbing wall received positive comments from the participants" [17].

While the previous methods required an instrumented climbing wall, the work by Ladha et al. utilizes wrist worn sensors to assess the climbing performance of the user [21]. The data from the wrist worn accelerometer sensors is automatically segmented into climbing sessions and moves. Based on this, parameters like power, control, stability, and speed of the climber are derived. To evaluate their system,

Figure 2.8.: Augmented climbing wall. Kajastila & Hämäläinen used projectors and a 3D camera to augment a climbing wall [17].

Ladha et al. collected data from 47 climbers during a competition. Fourty participants handed in a score sheet which was then used to compare the predicted score based on the parameters above and the actual competition score. The results showed a positive correlation between the predicted and the actual score.

In contrast to the system by Ladha et al., the purpose of this thesis' system is not to assess the skill of the climber, but rather automatically detect which routes she is climbing during a session. A prestudy conducted with 92 climbers should give insights in the participants' usual self-tracking behavior and how such a system could be beneficial for their training experience.

2.6. Summary and Conclusion

While Quantified Self seems like a marginal group, patterns of their tracking habits can also be found in the daily routine of ordinary users. Activity trackers like the fitbit, enable users without expert knowledge to track activities during their daily live. Many of these tracking devices incorporate a smartphone application which principally serves as user- or data visualisation interface since the tracking devices usually lack a large screen.

Since people track sports like running and cycling, it can be assumed that people would also track their climbing activities. This assumption is investigated in Chapter 3 which shows that some climbers already keep track of their climbing progress. The *tracking device and smartphone application* paradigm could also be used in the route recognition system described in this thesis. While the climber would not necessarily need the smartphone application to use the device, it could leverage the climbing session with additional information like a check list of already climbed routes.

The insight in the presented motivation types for tracking could be used to develop multiple usage modes of the recognition system. *Directive Tracking* could be used within a virtual training coach that guides the climber to the next skill level. The recording of training datasets, which are needed for robust route recognition, could be leveraged using the *Rewards* motivation: a user can gain achievements like badges or coupons for free drinks or admission in the climbing gym. Considering services like *humanapi.co* and *ginger.io*, parallels can be seen when applying Quantified Self methods as they are described in the scenario (see Chapter 1). The collected climbing data could give the climbing gym operator insights about the usage of specific climbing routes.

Considerable research was done concerning automatic activity tracking. The proposed papers suggest that the usage of accelerometers and gyroscopes attached to the sport device or the users herself is a common and proven method for activity tracking. In addition to the research in tracking technology, the related work showed that using a tracking system could improve the performance of the user. This could also be used in a future implementation of a virtual climbing coach, which would be based on the climbing data, assessed by the system proposed in this thesis.

Climbing did not find much attention in sports tracking. Some research topics include work to technology aided route creation, instrumented climbing walls, and automated skill assessment. Especially the latter is from particular interest. Ladha et al. used wrist worn accelerometer sensors that can analyze the climber's performance during an ascent [21]. This includes parameters like power, control, stability, and speed. These parameters are a good indicator for the performance of the climber, which was proven by predicting the climber's score in a bouldering competition.

Although the knowledge about the climber's performance is very helpful, it cannot assess the type of route the user climbed. The system proposed in this thesis is able to automatically recognize and track the routes a user is climbing during a climbing session. In contrast to a smartphone application, the system does not hinder the climber in her movements, nor does it require any user interaction.

3. Prestudy

3.1. Aim

A current survey[1] examined the available smartphone applications in the different markets (iOS, Android, Blackberry, Windows). The application categories *sports* and *healthcare and fitness* account for 7% of all applications across all common platforms . By way of comparison, the share of games is 23%. Few studies investigated why people are motivated to use such activity trackers and how regular use can improve fitness and health [5, 27, 30, 35].

To get initial insight on whether or not members of the climbing community are also tracking their sportive activities and if they even track their climbing progress, an online survey was conducted. The goal of the study was to get an impression in the habits of sports tracking, which sports are tracked, and in case of no tracking, why climbers do not track. This should give hints to what hinders people from tracking, despite they may be interested in the resulting data. Furthermore, the study should investigate whether climbers do currently track their climbing progress, if they are interested in it, and if yes, how they track their routes.

The main finding was that the sample *(N=92)* can be divided into two groups of climbers. The first group is represented by the climber how perform climbing out of leisure and relaxation purposes. They do not have any interest in quantifying their sport or even in the usage of technology. In contrast to that, the climbers of the second group track different sports and thus are also interested in tracking their climbing progress.

3.2. Procedure and Questionnaire Contents

The study was conducted through an online questionnaire. Facebook was used as the main communication channel to publish the study. Posting in several Facebook climbing groups helped to recruit only climbers.

The questionnaire (see appendix A.2) contained 17 questions, which were grouped in 5 categories as described in the following.

[1] `http://www.statisticbrain.com/mobile-phone-app-store-statistics/`

Personal Data assessed the age and sex, to give a basic insight about the participants.

General Questions to Climbing and Bouldering contained questions about the climbing experience, and the usual destination for climbing. For this, the participants were asked for how many years they have been climbing or bouldering. To assess the climbing and bouldering locations, the participant had to select a point on a 10 point scale which ranged from ”outdoors“ to ”indoors“. The selected point represented the ratio between the two locations. A value in the first quarter of the range would indicate that the participant spends most of her time outdoors.

General questions to sports tracking asked the participant which smartphone application or physical devices (fitbit, sports watch) they used and which sports they are tracking. In case of a negative answer, the participant was also asked for the reason (i.e. “why are you not using a sports tracker”).

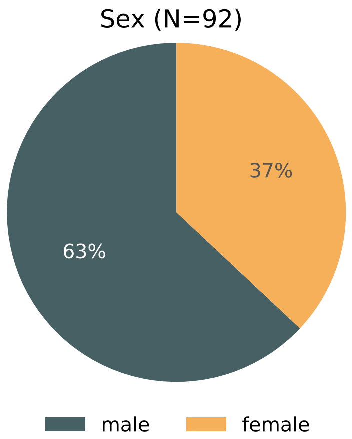
General questions to sports tracking and climbing aimed for information whether climbers track their routes they are climbing and how they do that. As in the questions above the participants were also asked why they do not take notes of her climbing progress. Additionally it was asked if the climber would use a system that tracked the routes automatically which she has climbed during a climbing session, or which manual actions would be acceptable to obtain a semi automatic tracking approach.

Final questions asked whether it is more important for the climber to assess which routes she climbed or how she climbed the routes (e.g. static, dynamic, speed, etc.). The final question was, if the participant had ideas how different technologies could be used for climbing training.

3.3. Results

3.3.1. Demographics and Climbing Habits

Altogether, 92 climbers participated (34 female, 58 male), with an average age of 29.8 ($SD = 8.5$). Although the age distribution is not normally distributed, the sample provides a broad age range, reaching from 16 to 62 years (see Figure 3.2). The average climbing experience was 5.6 years ($SD = 7.57$) while the average bouldering experience was 3.1 years ($SD = 4.76$) (see Figure 3.1). When asked for the usual location of climbing or bouldering the participants had to pick a point in the range from 1, representing outdoors to 10, representing indoors. While most climbers (53/39) tend to climb outdoors, bouldering is performed mostly indoors (63/29) (see Figure 3.3).



	AVG	SD
Age	29.87	8.53
Climbing since (years)	5.59	7.57
Bouldering since (years)	3.08	4.76

Figure 3.1.: Demographics of the survey. Altogether 92 climbers participated in the study (34 female, 58 male).

3.3.2. Tracking Methods and Tracked Sports

When asked which type of tracking the participants used, 51% stated that they did not use any tracking at all, 14% tracked only with a device, 17% used only an application, and 17% used both (see Figure3.4). The kind of sports which were tracked with the help of applications or devices varied from running and cycling to more unusual sports like kayaking or hang gliding. The majority was represented by running on the first place and cycling on the second place. A complete statistic of tracked sports can be seen in Figure 3.4.

As varying as the sports, the use of different tracking devices and smartphone applications was diverse. Amongst the devices, sports watches with 45% followed by handheld or mounted GPS devices with 33% formed the majority (see Figure 3.6). A leading position in smartphone applications was taken by the app *Runtastic* which

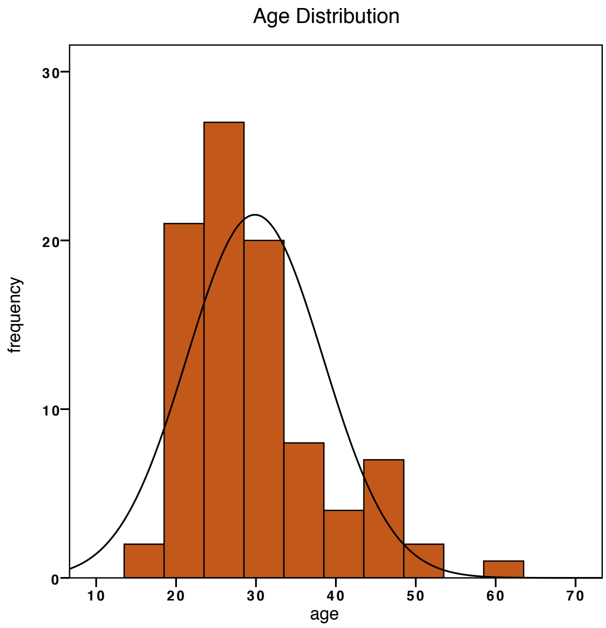


Figure 3.2.: Age distribution. Although the age distribution is not normally distributed, the sample provides a broad age range, reaching from 16 to 62 years.

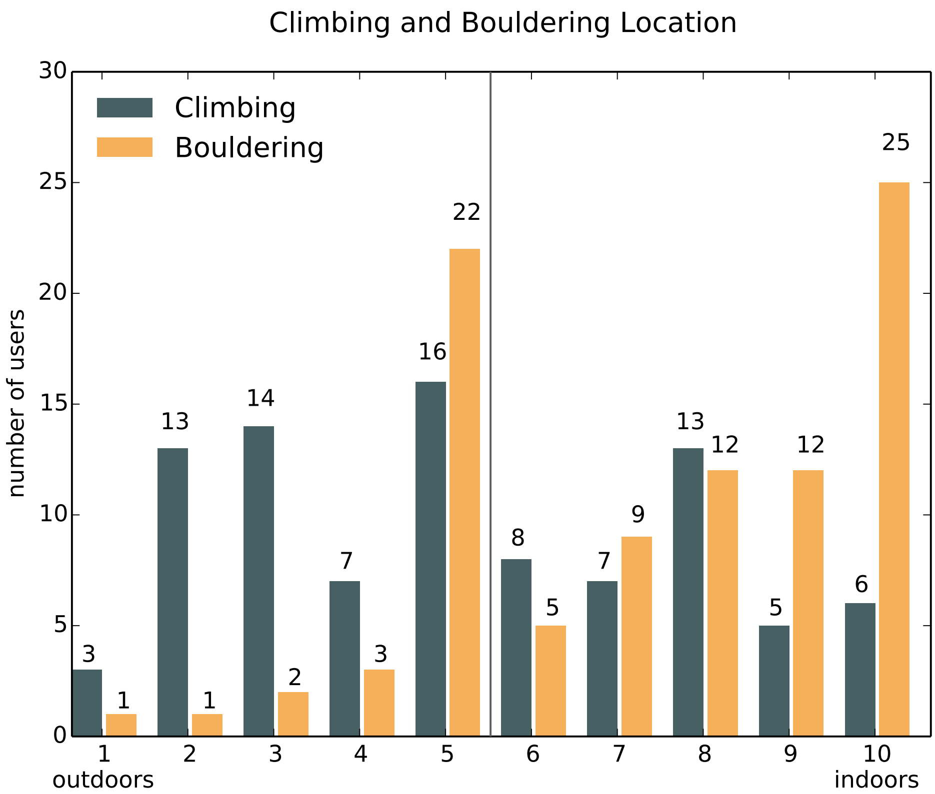


Figure 3.3.: Climbing locations. The participants were asked to state their usual climbing location on a 10-point scale, where 1 = outdoors and 10 = indoors. While most climbers (53/39) tend to climb outdoors, bouldering is performed mostly indoors (63/29).

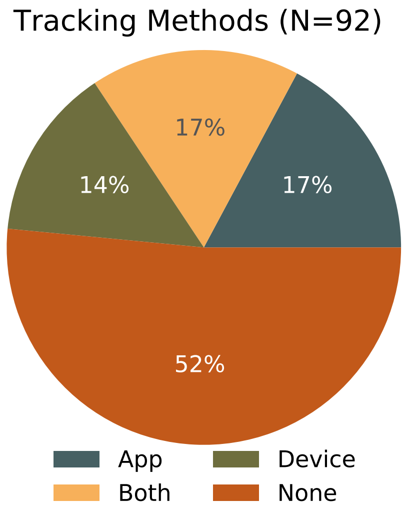


Figure 3.4.: Sports tracking methods. The participants tracked their sports in various ways. They used smartphone applications, devices like sports watches or even both. However, the majority of climbers does not track at all.

can be used, among others, for running and cycling. Altogether, 12 different applications were used by the participants (see 3.7).

Whenever the participants stated that they did not use a device or a smartphone app they were asked for the reason. In both cases most of the participants stated that they did not use any of them because they are not interested in the data. Another large part purposely refrained from using a tracking system because they would do the sport for fun and recreation, and not for training reasons which would justify the use of such systems. Concerning the tracking devices, one of the main reasons not to use them, was the price. The fear of breaking a smartphone was another cause that kept the participant from using smartphone application for tracking purposes.

Twenty-two participants used online portals to manage their activities. Most of them used a corresponding portal to the smartphone application (e.g. Runtastic, Strava) as also the corresponding portals from tracking devices (e.g. Garmin Connect, Suunto Movescount). The main reason for not using such a portal was the missing interest in the accumulated data. One participant stated that she does not trust the provider and that she wants to keep her data for herself.

3.3.3. Tracking and Climbing

As mentioned in the beginning, the participants formed two groups: People who track and people how do not track at all. Nevertheless, there are climbers who track their climbing progress but no other sport. When asked how they keep track

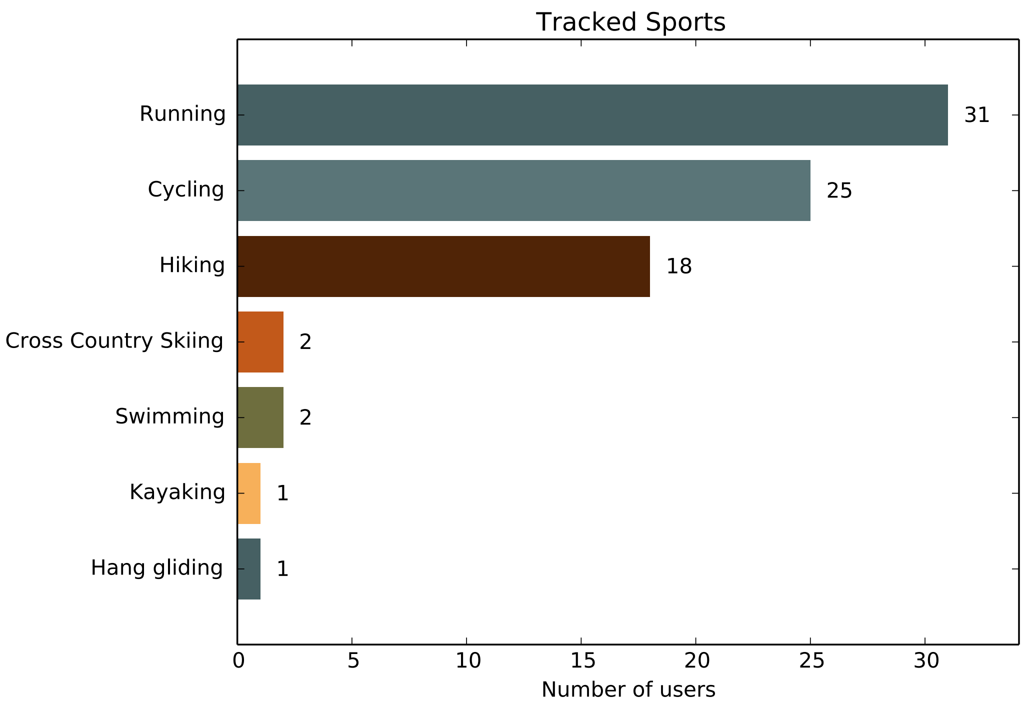


Figure 3.5.: Sports tracked by the participants using devices and applications.

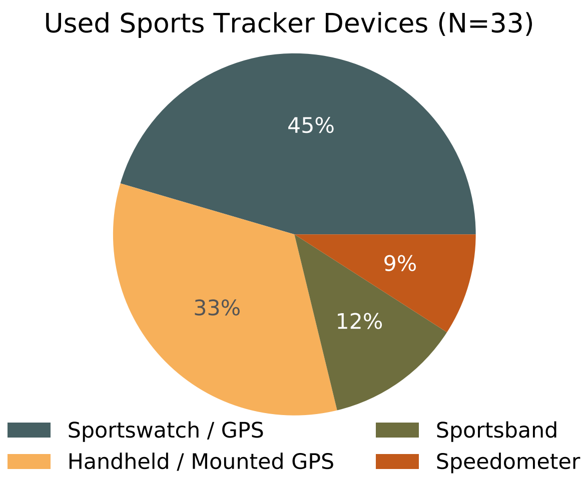


Figure 3.6.: Sports tracker devices used by the participants.

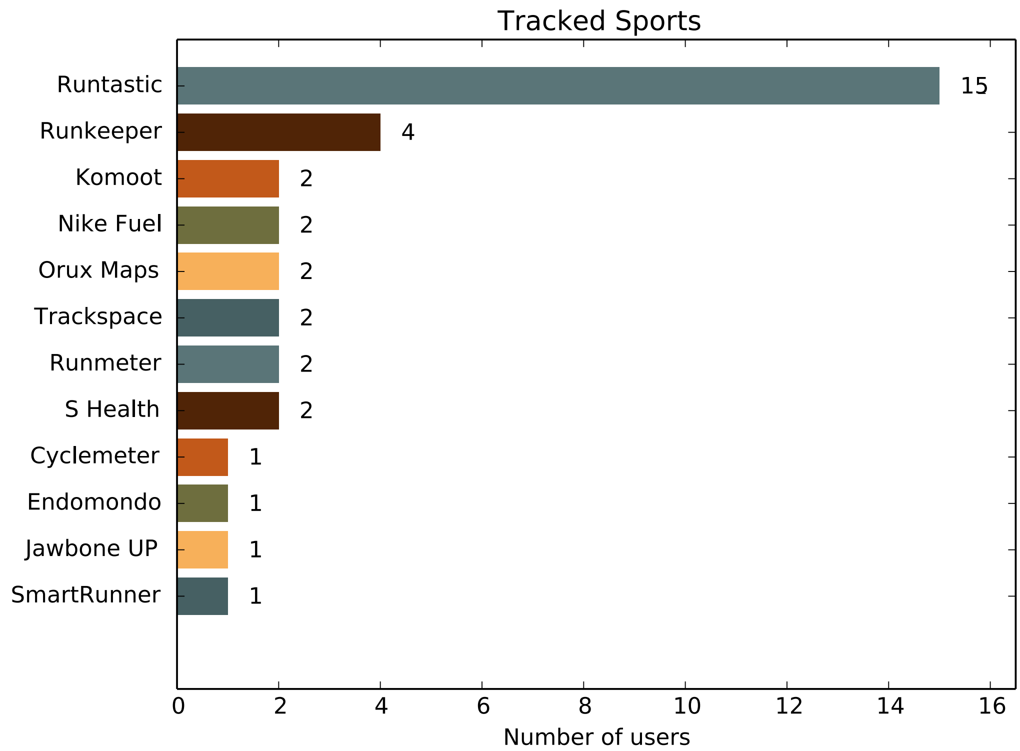


Figure 3.7.: Sports tracker apps used by the participants. Each participant was allowed to name multiple apps.

of the climbed routes, the following methods were proposed. Noting of routes in the guidebook which is used for outdoor climbs formed the majority with 45%. Spreadsheets and sports diary were represented with 23%. The method to write the routes down with a pen on a piece of paper or in a book took 19%. Smartphone applications or online portals like `8a.nu` completed the set with 16% (see Figure 3.8).

When asked why they did not keep track of their climbed routes, most of the participants stated that they do not see a benefit in it, since they could remember the routes they have climbed. Another reason that was stated multiple times was that it would be too cumbersome and time consuming. As in the question concerning general tracking, some participants stated that they are climbing for fun and thus, would like to spend the time climbing and not tracking.

The 54% which would not use an automatic tracking system stated that they are not interested in the data. Even an automated system would be too cumbersome for some participants. Another climber stated that such a system would only be useful if used during every climbing session. Some participants stated that it would be not worth the effort since they are beginners or are not climbing enough. They supposed that such a system would be more useful for competitive climbers.

The participants who where not reluctant against tracking were asked what would be more important to track: which routes the participant is climbing or how the participant is climbing. Most of the participants (M = 7.05, SD = 2.32, where 1=routes and 10=style) stated that the style, e.g static, dynamic, or fast would be more important for them than the number or of routes they climbed. 46% of all the participants (this also includes the participants who do not track at all) would use an automatic tracking system. As possible manual interactions the participants would accept the press of a button on a wristband, scanning of a QR code with the smartphone, selection of a route in a smartphone application, or even a manual entry of an ascent. One participant stated that he would select the route on the smartphone with the premise that the wristbands would record his climbing style during the ascent.

3.3.4. Technology and Climbing

The feedback on how technology could enhance climbing was quite varied. Some climbers suggested using a smartwatch that could guide the climber to the next hold / foothold. Sensors could be attached to the climber's arms and legs to sense how efficient they perform. Another idea was that theses sensors could also determine which part of the route leads to an unstable position. An application could propose a motion sequence which would solve this problem. Pulse sensors could assess the level of effort during an ascent.

Several participants addressed statistics and virtual trainers. One participant described a system that would suggest routes that he did not yet climb, but would be able to, based on his climbing history. His climbing history would be compared to other climbers which already climbed the suggested route. Many climbers requested a functionality which would be able to record the length of a route, time spend in the

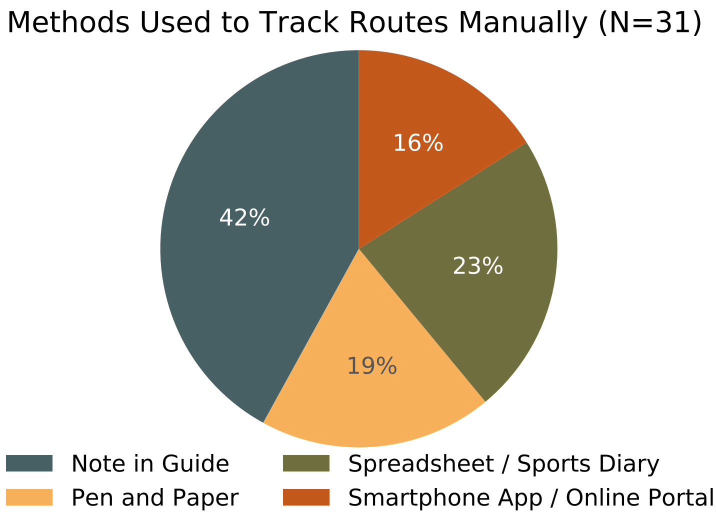


Figure 3.8.: Methods used to track routes manually.

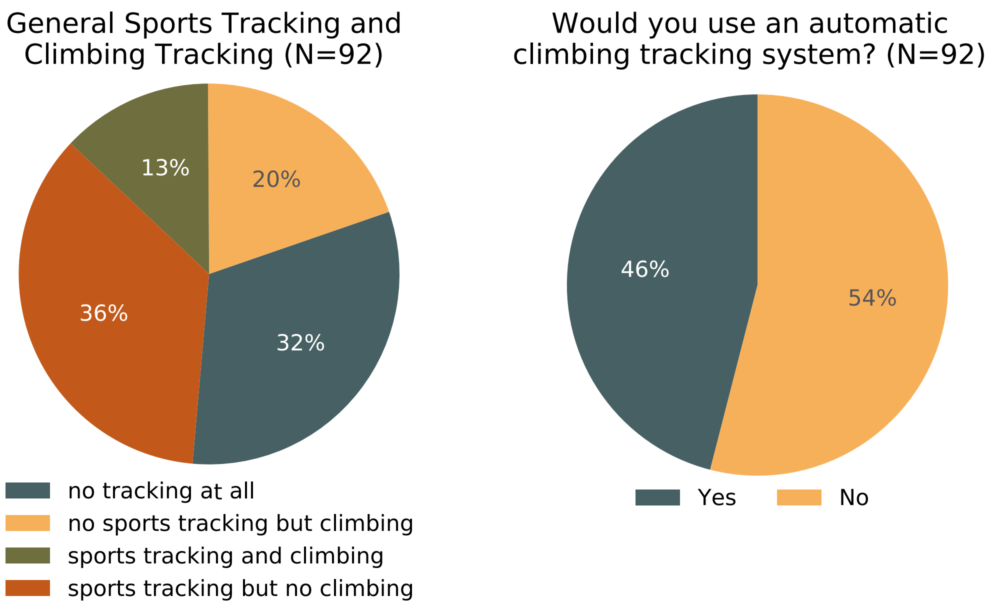


Figure 3.9.: Tracking in general and tracking of climbing. The majority of the participants do not track at all but there are climbers who do track climbing but no other sport.

route and general statistics to climbing sessions and progress over time. One user stressed that it would be possible to create an objective difficulty measure instead of the currently used more or less subjective ones, based on the success or failure of cumulated ascents.

3.4. Summary and Discussion

The results described above show that some of the climbers are willing and/or are currently recording the routes they already climbed. Some of them also mark down the routes that they consider as a project for the future. Many of the climbers stated that they would track other sport activities, but that it would be too cumbersome to track all the routes they are climbing. A system that motivates this group of climbers would have to be responsive with a sleek interface that enables the user to perform the tracking task in a minimum number of steps. This could be, for example, a smartphone application which provides, besides the tracking functionality, an additional value such as more detailed information of a route (e.g. how often did I / my friends climb the route, the route has long movements or small holds) or exhaustive statistics.

Using their mobile phone is not an option for some of the participants, since they fear to break the phone or hurt themselves in case of a fall. This group of climbers could benefit from a body worn system that records the routes they climb fully automatically with no user interaction at all.

The second group of participants are the ones who do not track at all. This group would be the hardest to motivate to use a tracking system for climbing. Most of them do not track out of persuasion, since for them, climbing is a sport which should be performed without consumer electronics. One should consider if changing the attitude of those climbers is a goal which should be pursued.

A more promising group of climbers, which are currently not tracking, is beginners. Novice climbers stated that it would not make much sense to track the routes they are climbing, since they are currently only beginners with little expertise. A system which tracks all the routes a climber performs during a session could also serve as a virtual coach as in [19]. It could track the progress of the climber and push her into routes she would not climb because of unfamiliar movements. This is in fact a common training technique [15].

Resulting from the insights above, the following requirements for an automatic route recognition system could be identified. Concerning the first group, the system should not be depending on a smartphone which would have to be carried around. Furthermore, the system should not hinder the movements of a climber during an ascent. Since some climbers stated, that continuous tracking of routes would be too cumbersome, the system would have to automatically track the routes without any interaction of the user.

As a result, the optimal solution would be combination of wristbands that do not require any user interaction, and a smartphone application which gives more possibilities during or after a climbing session. The wristbands are usable without the smartphone and automatically track every route the user is climbing during a climbing session. A smartphone application could be used to visualize the data that is collected by the wrist bands. The combination of physical device and smartphone application is a proven concept which is shown by the fitbit, the Nike+ Fuel Band and other activity tracker devices. All of those use additional applications that are able to summarize and visualize the tracked activities.

The following chapter describes the concept and implementation of wrist worn inertia measurement units. Using the sensor data which is recorded during an ascent it is possible to recognize the route a user is climbing.

4. Automatic Climb Recognition

4.1. Introduction

The aim of this thesis is to find a way to automatically recognize the routes that a climber completes during a climbing session. For this, it is crucial to define the characteristics of a route. The system uses the assumption that the characteristic of a route can be defined by a number of several ascents.

Sensors, which are attached to the climber's wrist, record the acceleration of the limbs. With the help of a sensor fusion algorithm, the orientation of the arms are determined. This algorithm calculates the orientation by fusing the accelerometer, gyroscope, and magnetometer readings. The system detects the movements throughout a climb and can distinguish between the transition from one hold to another as well as the gripping of a hold itself. Whenever a hand rests on a hold, the different orientation of the arm is recorded, which represents one of the ascent's features. These different positions evolve from the various hold types like side pulls, underclings, jugs, or crimpers, which are all mounted in different heights. An ascent is characterized by two sequences, one for each arm. Every sequence consists of a number of arm orientations that are obtained during the climb as described above. Usually, the length of each sequence equals to the number of holds the respective hand grabbed throughout the ascent of a specific route. A route can only be sufficiently described if enough datasets are recorded because a route is not always climbed by the same person and in the same style. This results, depending on the height of the climber, in different limb positions.

To recognize a newly climbed route, the dataset that evolves from the ascent is processed as described above, resulting in two sequences of orientations. These sequences are interpreted as strings of symbols, where each symbol represents an orientation of the limb. The new dataset is now compared to training datasets that were recorded beforehand. As a comparison measure a word edit distance is used. This distance specifies the number of edit operations (insert, delete, replace) which are needed to transform one word into another. In this particular case, a weighted Levenshtein distance is used to compare one orientation sequence to another. This comparison is done for each training dataset where the dataset with the lowest edit distance is considered as winner, thus identifying the corresponding route to the new, unrecognized dataset.

The following sections explain this process in detail. Section 4.2 describes the setup and design of the sensor armbands. An Arduino in combination with a 9DOF inertia measurement unit (IMU) and a SDCard writer is used to log the raw data from the sensor which is then processed in the subsequent steps. The processing is performed by the analytics toolkit that also serves as interface for visual analysis of the collected data. This toolkit and it's features are introduced in more detail in Section 4.3. After downloading the raw data into the system, the data is pre-processed by filtering and the calculation of the orientation via the sensor fusion algorithm. Section 4.4 explains the detection of movements and grips, which is done by applying multiple thresholds on previously calculated windows of data frames. The individual grips are then converted into symbols, representing the corresponding orientations of the arms during a grip. In the string matching phase, the individual string of sequences of a new, unrecognized route is compared to a number of training datasets which was recorded for every route beforehand. The training dataset with the smallest edit distance to the new, unrecognized dataset defines the resulting route.

4.2. Sensors

As mentioned in [7], commercial accelerometer driven products like the fitbit or the Nike+ FuelBand do not provide access to the raw data collected by the device. The missing API of commercial devices and the need for additional data like the orientation of the sensor required to build a custom prototype of a sensor armband.

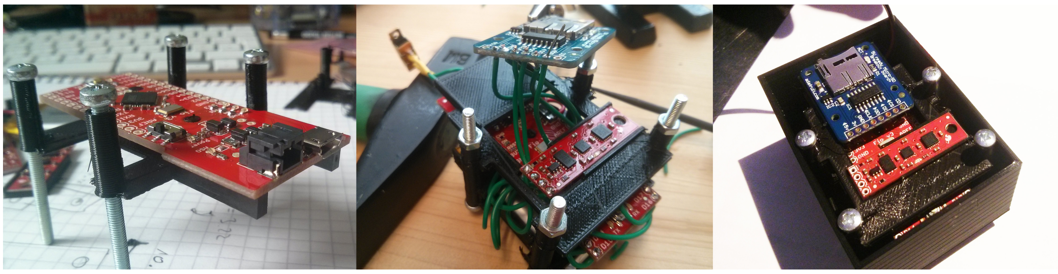


Figure 4.1.: Mounting for the sensor modules. Left: Arduino Fio. Center: SDCard writer and sensor stick. Right: all modules assembled in the housing.

4.2.1. Hardware

The prototype uses a Razor 9DOF Sensor Stick containing a triple-axis gyroscope, a triple-axis accelerometer, and a triple-axis magnetometer. This sensor allowed to assess the orientation. A microSD card writer was used to store the sensor readings during the climbing sessions. Both components were driven by an Arduino Fio v3 with an ATmega32U4 chip and a rechargeable battery. The sensor box could record approximately three hours of climbing with a fully charged battery.

Since the sensor should be worn on the wrist, a 3D model of a housing was designed using OpenScad[1] and printed with an ultimaker[2] 3D printer. As it can be seen in Figure 4.1, stackable frames were used to hold the individual modules in place. Figure 4.2 shows a rendering of the single frames and the housing. This setup also allows later extensions of the prototype by muscle or heart rate sensors. The frames were held in place by off-the-shelf nuts and bolts inside a custom built housing. This housing had the dimensions of 7cm × 3.5cm × 5cm. A leather strip with velcro was used to fix the sensor boxes on the wrist of the climber (see Figure4.3). The sensor bands have to be fixated relatively tightly to avoid slipping of the box during a climb.

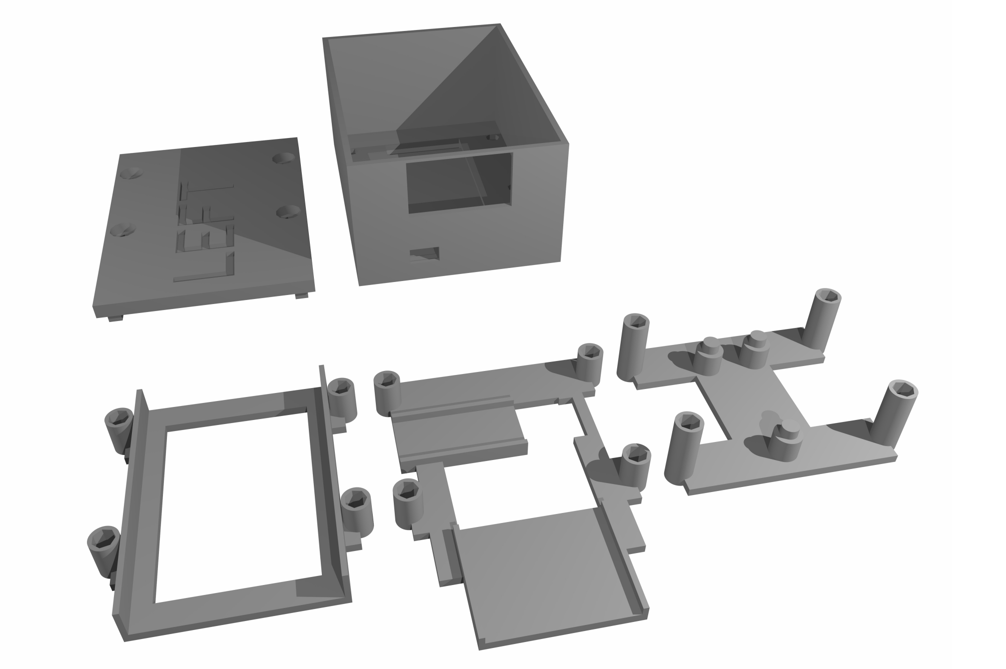


Figure 4.2.: Rendering of the sensor box. The components of the sensor box were mounted on the corresponding frames. Left: battery, center: sensor stick and SDCard writer, right: Arduino.

4.2.2. Firmware

The orientation of the sensor stick, which corresponds to the orientation of the arm, are calculated using a sensor fusion algorithm provided by an open source project[3].

[1] http://www.openscad.org/
[2] https://www.ultimaker.com
[3] https://github.com/ptrbrtz/razor-9dof-ahrs

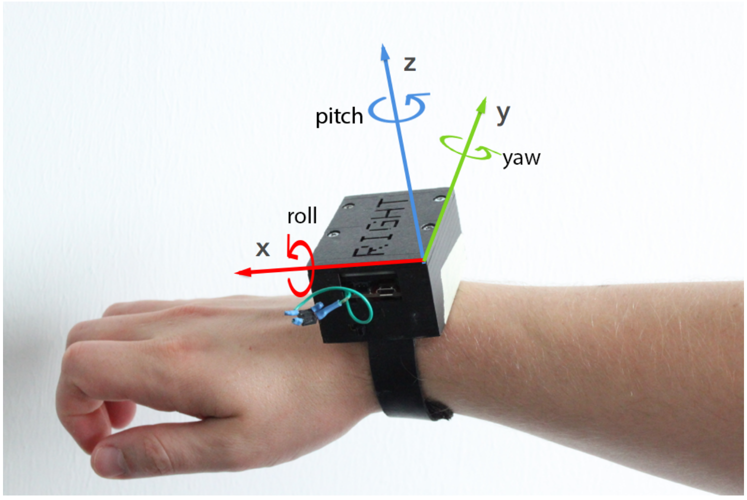


Figure 4.3.: Sensor box attached to wrist. The attached button is used to manually mark timestamps in the recorded data. The x-axis runs parallel to the arm which is later used to determine if the arm is pointing up- or downwards. Yaw, pitch, and roll corresponds to the y-, z-, and x axis.

The algorithm fuses the three sensors to provide a stable orientation even when acceleration is applied. Additionally, the firmware was extended in a way so that a press of the external button of the sensor box logs this event within the stream of collected data. The sensor fusion algorithm provided by the open source firmware originally ran on the Arudino itself. The need for data logging on the internal SDCard exceeded the flash memory limit of the Arduino, which made it necessary to calculate the orientation offline on a computer. For this, the Arduino code was ported to be used as a self-contained command line utility that processes the raw data downloaded from the SDCard. All three sensors, the accelerometer, the gyroscope, and the magnetometer needed to be calibrated. Concerning the accelerometer, $1g$ (i.e. earth's gravitational pull) was not defined by a predefined sensor reading. To calibrate the accelerometer, the sensor reading has to be assessed without any external acceleration. For this, the sensor box was placed in the direction of each axis and the resulting value was recorded one by one. To calibrate the gyroscope, the average rotation reading in a period of ten seconds was assessed. During this period the sensor box should not be moved. For calibration of the magnetometer as special application was provided by the developer of the algorithm. The sensor box had to be rotated around it's axes to cover a sphere. After that, the application calculated parameters that were used in the sensor fusion algorithm. These parameters helped to compensate hard and soft iron errors. Hard and soft iron errors are caused by screws, batteries, or cables and result in a distortion of the magnetic field which would lead to drifting. With the help of the calibration these distortions can be neutralized. The calibration parameters had to be assessed for each sensorbox and were hard coded into the command line util.

After processing, each data frame consisted of a timestamp in milliseconds, the raw information obtained from the three individual sensors (accelerometer, gyroscope, and magnetometer) for all three axis, the calculated orientation (yaw, pitch, roll), and the state of the external button. An example line of the processed data can be seen below.

```
T,94,
A,-207.607,-51.2,119.726,
G,0.490002,30.24,15.64,
M,-232.726,37.0698,499.041,
Y,-69.9776,P,67.2499,R,-19.006,
A_R,-225,-42,90,
B,0
```

For readability reasons the line is wrapped. T indicates the timestamp in milliseconds, A corresponds to the accelerometer data, G to the gyroscope and M to the magnetometer data. While these values are calibrated as stated above, A_R contains the raw accelerometer data that are used in later processing. The next three values depict the Yaw, Pitch, and Roll angles, while the last value describes if the external button is pressed or not. Figure 4.3 shows the resulting coordinate system, where yaw, pitch, and roll is bound to the y-, z- and x-axis.

4.3. Analytics Toolkit

The preprocessed data is now stored within the analytics toolkit. This toolkit has two main functionalities. First, it suits as a video/data analysis interface and secondly provides a framework for the processing and recognition of climbing data. It is based on a Django[4] installation, which is a python framework for web applications. Django was chosen as development framework since it provided a good tradeoff between easy user interface design and a rather powerful programming language. Furthermore, HTML5 in combination with JavaScript has turned out to be a very efficient and easy to customize combination to produce a user interface for data inspection. A screenshot showing the simulation view can be seen in Figure 4.4 on the following page. The interface allowed the manual inspection of the data that was delivered from the sensors. WebGL was used to render a simulation of the sensor boxes showing the current orientation in synchronisation with the playing video. Additionally, a plot of the current acceleration in X and Y direction was used to understand the incoming data.

Besides the advantage of easy user interface development, the collected sensor data was stored in a custom database that allowed an appropriate design for organization. This included assigning the collected data to participants, attaching

[4] https://www.djangoproject.com/

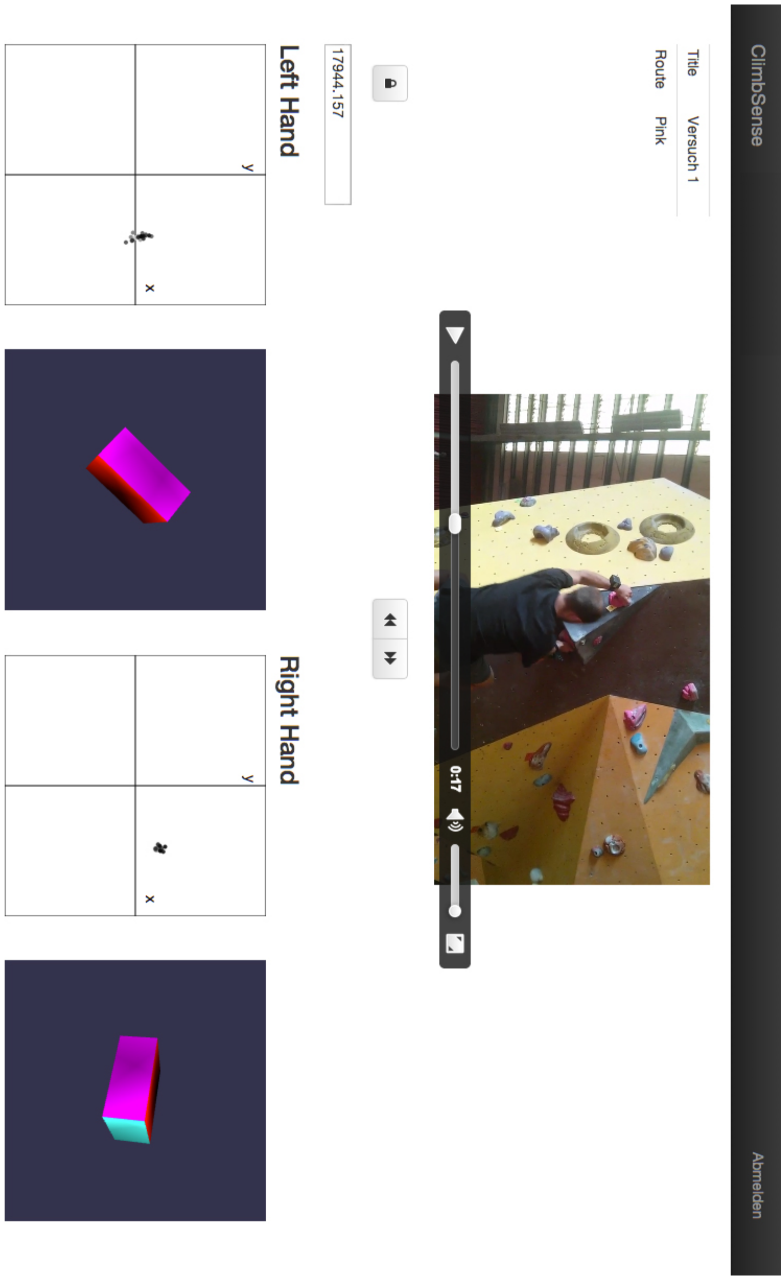


Figure 4.4.: Video analysis interface showing a rendering of the sensor boxes in synchronisation with the playing video.

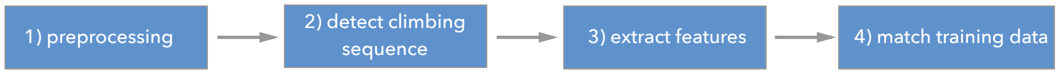


Figure 4.5.: Overview of route detection algorithm. The training data creation corresponds to the first three steps.

tags to datasets, and setting up routes and boulders that were also later linked to datasets. The data were then used by several consumers, like the before mentioned video analysis interface, the recognition process (see Section 4.4), and the evaluation (see Chapter 5).

In the future, it would be possible to extend the system by a public web application, that shows the user's climbing history and statistics.

4.4. Recognition Process

As described in Section 4.1 the recognition process relies on characterization of the routes by multiple ascents. The features of a route are extracted from the orientation of the arms at each time the hands are resting on the holds during the ascent of a route. These orientations form two sequences, one for each arm. Both sequences represent a part of the route's fingerprint. Although many routes consist of a characteristic set of holds (side pulls, underclings, jugs) in different orientations and positions, an ascent varies because of the climber's height, her climbing style, and if she uses all available holds, or skips some. This problem is solved by two methods. First, not only one but also several datasets are recorded for one route, resulting in a more representative route characterisation. Secondly, the matching algorithm described later allows a certain degree of deviation. The route recognition process is based on the gesture recognition method proposed by [34]. Stiefmeier et al. considered gestures as strings of symbols that encode motion vectors. With their method they could successfully spot gestures during a bike maintenance task. Each task was assigned a training string, which was then matched to new incoming data (already converted to a string) with the help of a weighted Levenshtein distance. The Levenshtein distance is an edit distance which describes the difference between two strings. It is defined as the minimum number of required edit operations (insertion, deletion, or substitution of a character) to transform one string into another.

Figure 4.5 shows an overview of the route recognition process which is described in more detail in the following subsections. In a first step, (1) the raw data coming from the sensor boxes is preprocessed as described in subSection 4.2.2. This includes filtering and orientation calculations. After that the climbing sequence is detected (2) by calculating the movement energy within a data window, whereas low energy corresponds with a hand fixating a hold and high energy with the transition from one hold to another. The feature extracting step (3) calculates the sequence of arm orientations which arises during the ascent of a route. In the last step, (4) the resulting string from the feature extraction is matched against the training data with the help of a weighted Levenshtein distance.

4.4.1. Preprocessing

After downloading the sensor data from the SDCards, the raw accelerometer data is filtered with a discrete first-order low-pass filter. The following equation is used for the calculation:

$$
\begin{aligned}
&r : \text{raw data} \\
&f : \text{filtered data} \\
\\
&f_1 = r_1 \\
\\
&\forall t > 1 : \\
&f_t = 0.3 * f_{t-1} + 0.9 * r_t
\end{aligned}
$$

The filtered data is then discretized using a sliding window procedure with a total window length of 14 frames and an overlap of 4 frames, 2 on each side. The used parameters were assessed by experiments. A frame is recorded every $20ms$ resulting in a total window length of $280ms$. The number of frames per second is given by the used hardware. Next, the average and the standard deviation of the three accelerometer values is calculated for each window. The sum of the standard deviations serves as description of the window's energy, that is later used for the differentiation between gripping a hold and the transition from one hold to another. In the following, only sequences of windows instead of individual frames are considered except otherwise stated.

4.4.2. Climbing Sequence and Grip Detection

Each recording of a dataset only contains one climbing sequence. This also includes standing on the ground, the ascent itself, and lowering, in case of sports route.

A climbing sequence is defined as an alternation between little movement and high movement where the first corresponds to the grip of a hold and the latter corresponds to the transition from one hold to another. Analog to this definition, the segmentation of individual movements is achieved by applying two thresholds t_{low} and t_{high} on the energy (i.e. the sum of the standard deviations) for each window. An alternation between those two thresholds indicates a movement thtat is set as property of the window ($is\_gripping\_window$). A second pair of thresholds is applied to the x-axis (parallel to the climber's arm) acceleration indicating whether the arm is pointing down (t_{down}) or up (t_{up}). After identifying the movements and arm position in the dataset for the left and right hand, the climbing sequence is narrowed down by observing both arms simultaneously. For this, both window sequences (left hand

and right hand) are iterated and flagged with *both_hands_down* or *both_hands_up* whenever in two corresponding windows (two windows correspond if they share the same timestamp) the arms are pointing up or down.

The thresholds were determined automatically by running an analytics script over a set of recordings. For this, the actual number of grips was manually transcribed from the video and annotated. An interval ranging from a relatively low to a relatively high energy was assigned to each threshold. After iterating over all values within these intervals, the script returned the "best" combination of thresholds. The "best" combination is defined as the set of thresholds which result in the smallest delta between the actual number and the detected number of grips.

In a final step, the climbing sequence within the recording is marked by applying the definition above. The mentioned thresholds were determined by experiments that were ran automatically. Figure 4.6 shows a plot of a route's recording with the hold transitions and the boundaries of the climbing sequence indicated as red triangles and pink squares.

The result of this step is two sequences of groups of windows which were marked as gripping windows. These sequences are now used to extract the features of this ascent and are defined like the following.

$$[[frame_0, \dots, frame_m], \dots, [frame_0, \dots, frame_n]] \tag{4.1}$$

4.4.3. Feature Extraction

The method of gesture recognition as proposed by [34] uses a codebook to convert the direction vectors which were calculated from accelerometer data into symbols. A codebook is basically a mapping from a set of values to one single value or symbol. A sequence of those symbols forms a string. This string is then considered a word, which can be used to calculate the Levenshtein distance between two "stringified" gestures.

This method is adapted in the route recognition process. Instead of direction vectors, arm orientations, which arise during the ascent of a route, are used. These orientations are fetched whenever a hand grips a hold. An orientation is converted with the help of a codebook into a symbol representing the yaw, pitch and roll angles. The codebook is generated as follows. First, a circle is divided into 30 segments. One segment represents a 30th of 360°, which results in segments covering 12°. Thirty segments give a satisfying tradeoff between generalization and sufficient discriminability. This step has to be executed three times, one time for each of the three angles (yaw, pitch, roll).

For a better understanding of this procedure, consider the following example: to convert a specific orientation of the sensor box, the matching segment for each angle is chosen. Suppose we have the orientation $yaw = 50,\ pitch = 125,\ roll = 10$ then the resulting segments for the three axis would have the indices 4, 10, and 0 (see Figure 4.7 on page 43). Using this method, an orientation of a sensor box can be

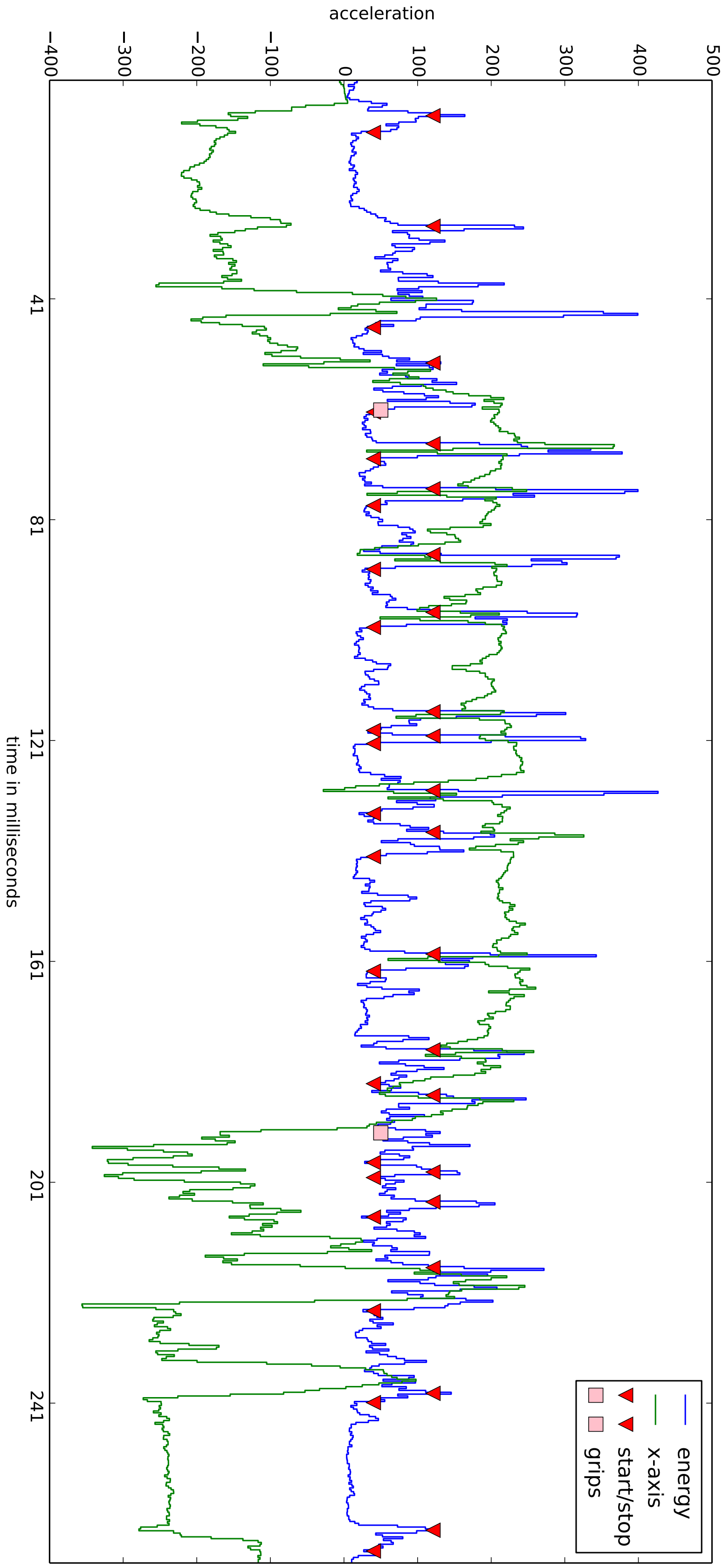


Figure 4.6.: Recorded data (left hand) of a top rope climb. Blue: sum of standard deviations, green: mean of x-axis acceleration, red triangles: thresholds for move segmentation, pink squares: start and stop of climbing sequence.

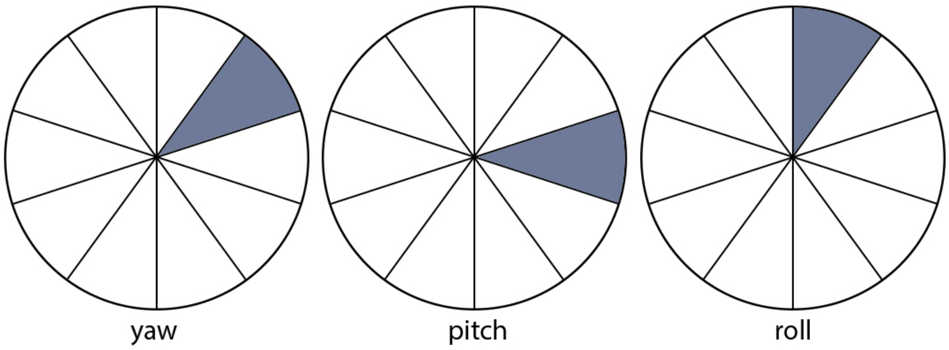


Figure 4.7.: Segmentation of the orientation $yaw = 50°$, $pitch = 125°$, $roll = 10°$. One segment spans an interval of $[i \times 36, (i+1) \times 36 - 1]$. For the sake of simplicity, the number of segments was reduced to 10.

coded into one of $30 \times 30 \times 30 = 27.000$ resulting symbols. During recognition each orientation is assigned to a combination of segment indices.

The following paragraph explains the processing of only one data sequence, e.g. the sequence of the left hand, to complete the recognition this procedure has to be repeated for the right hand.

As mentioned before, the result of the previous step are two sequences containing groups of windows that were marked as gripping windows. Each group of these windows contains the one window that holds the frame from that the orientation of the arm has to be extracted. This frame is chosen out of the middle of the window with the lowest energy. The intermediate result is a sequence of frames where each frame corresponds to a grip of the hand during the ascent. Each position, which is stored in the frame, is now encoded with the help of the codebook described above. A string describing the position of the left hand during an ascent of a route could look like this:

```
["1,28,9", "4,23,28", "28,24,4", "5,24,28", "2,25,4", ...]
```

4.4.4. String Matching and Final Result Generation

In a final step of the route recognition process, the route is determined based on the calculated strings. The general approach is to compare the incoming dataset with each of the training datasets that are stored in the database for each individual route. As comparison, a weighted Levenshtein distance is used [6]. The weighted Levenshtein distance used by the system is defined by the following equation.

$$
\begin{aligned}
m &= |u| \\
n &= |v| \\
D_{i,0} &= i, 1 \leq i \leq m \\
D_{0,j} &= j, 1 \leq j \leq n \\
D_{i,j} &= \min \begin{cases} D_{i-1,j-1} & +0 \mathrm{if} u_i = v_j \\ D_{i-1,j-1} & +0.1 \times SymbolDistance(u_i, v_j) \textit{ (Substitution)} \\ D_{i,j-1} & +1 \textit{ (Insertion)} \\ D_{i-1,j} & +0.1 \textit{ (Deletion)} \end{cases} \\
1 \leq i \leq m&, 1 \leq j \leq n
\end{aligned}
$$

SYM_DISTANCE depicts the distance between two symbols, i.e. two orientations. The symbol distance has to be included in the calculation, since the system should allow a certain degree of deviation. This need arises, since an ascent is not always performed in the same way. Skipping of holds or different grip positions produce a variation in every ascent, which is compensated by this method. The distance between two symbols is calculated by adding the encoded angle distance of all three axis, e.g. $dist([0, 0, 0], [0, 1, 2]) = 0 + 1 + 2 = 3$. Since there are always two possibilities to transition from one angle to another, the the shortest difference has to be chosen. As an example, consider a circle from its center two lines arise. Both of these lines have an outer and an inner angle. As a result, the distance between the two symbols $[0, 0, 0]$ and $[29, 0, 0]$ is 1 and not 29. See algorithm 4 on page 66 for a more detailed explanation.

To generate the final result, the incoming dataset has to be compared to the training datasets which are available for each route. For this, the Levenshtein distances between the strings for the left hand and the strings for the right hand are summed up, which results in a score for the pair of the two datasets (incoming and training). See algorithm 1 in the appendix for a better understanding. The pair with the lowest score is chosen as the winner. The smaller the score the higher the probability that the route was recognized correctly.

With the method described above it is possible to extract characteristics of a climbing route ascent which are then used to identify the climbed route. Characteristics of an ascent are defined as the arm positions that evolve whenever a hand rests on a hold. These orientations are generalized into symbols with the help of a codebook and thus form a string of symbols. Using a weighted Levenshtein distance, the strings of a new unrecognized dataset are compared with prerecorded training datasets. The match with the lowest edit distance defines the resulting route.

While this chapter explained the implementation of the system, the next chapter describes the evaluation of it. Different types of cross-validation are applied on a set of collected datasets.

5. Analysis of the Recognition Performance

5.1. Data Recording Study

The recognition performance of the system described above was evaluated in a user study. For this, participants were asked to climb a set of predefined routes, while wearing the sensor boxes. The resulting recordings of the single climbs were used for training and testing of the recognition system. For this, cross-validation methods were applied.

A final test investigated whether the data of only one sensor armband is sufficient for a satisfying recognition. This could be especially helpful when considering smartwatches. Instead of special wrist bands as used in this implementation, one single smartwatch could be used for the recognition and also immediate user feedback.

5.1.1. Participants

The climbers which participated in the data recording study were asked to answer the same background questions as in the prestudy (see Chapter 3). 8 climbers with different skill levels participated in the study, were one participant was female. In average the participants climbed for 7.25 years ($SD = 7.12$), ranging from four to 24 years. The participant's skill level ranged from IV to $VIII+$. Six of the participants stated, that they would rather climb outside than in a climbing gym. Bouldering was done since 5.8 years in average ($SD = 5.76$), ranging from three to 20 years. Five participants stated they would perform bouldering outside, while three participants are usually going in a climbing gym. Seven of the participants were right-handed.

5.1.2. Tasks

To build a data corpus, the participants were asked to climb a set of 5 predefined routes. The difficulty of the routes ranged from $IV-$ to $VI+$ (UIAA) and they contained dynamic and static moves, and different hold types. All routes had roughly the same number of holds and the same height. The routes were straight with no to little overhang. Each route varied in terms of holds in different forms and difficulty to grip. Furthermore, all routes were top-rope routes. In contrast to lead climbing, where the climber has to carry the rope and clip it in bolts attached to the wall, the rope was hanging from the top of the wall.

The participants were asked to climb each route two times. While the first ascent should make them familiar with the route, the second ascent should represent an

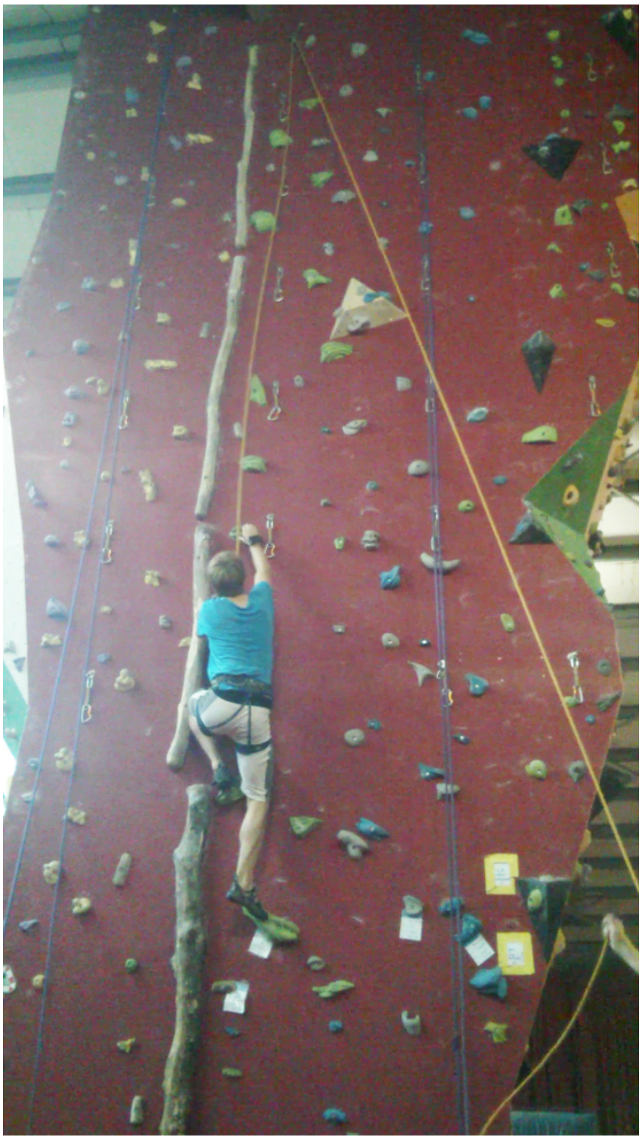


Figure 5.1.: Participant climbing a route.

Figure 5.2.: Wrist-worn IMUs. The external buttons where used to synchronize the data recordings.

ascent of a familiar route. No participant climbed any of the selected routes before. Both ascents were recorded. Since not every participant was able to climb every route during the recording sessions, the average number of recording per route was 10 ($SD = 3.53$). As a result, in total 50 recordings could be achieved.

5.1.3. Procedure

To assess the climbing data, the following procedure was performed for each climb. In a first step the participant had to put on the wristbands. Since the recognition of the route relies on the orientations of the arms, it was necessary to put on the sensors in the same way for each recording. The sensors had labels to distinguish between the left and right hand. Figure 5.2 shows the sensors, worn by a participant. After the participant tied herself in, the recording was started by simultaneously pressing the external buttons of the sensor boxes. This was necessary since the current prototype does not contain clock modules, which could be used for synchronisation in the future. Additionally a video recording was started, to compare the collected sensor data with the actual movements of the climber.

Each recording of the ascents lasted about 30 minutes per participant. The participants were allowed to take breaks as often as they wanted. When the participant had finished the route she was lowered. As a final step the recording was stopped by switching of the sensor boxes. The sensor data for each ascent was automatically written in a separate file on the internal SDCard. This files were finally uploaded via an API into the system. After assigning the routes to each of the recordings, the data was processed as described in Chapter 4.

5.2. Results

5.2.1. Grip Detection

The first step in the route recognition process is the detection of grips. To evaluate the grip detection of the system, five randomly choosen datasets were selected. For each sample the number of grips was assessed manually as a ground truth. This was done by counting the number of grips by analyzing the video recording. Finally this ground truth was compared with the number of automatically recognized grips. Table 5.1 shows the result of this assessment. For each ascent the actual number of holds per hand was assessed transcribed from the video and compared to the number of detected grips. The number of actual grips ranged from nine to ten while the recognized number of grips ranged from eight to twelve. Except for one record, the difference between the actual number of grips and the detected number of grips fluctuated between one and three. One record differed in five grips.

Ascent	LH (V)	RH (V)	LH (D)	RH (D)	S (V)	S (D)	Delta
1	10	10	11	8	20	19	1
2	10	10	11	11	20	22	2
3	9	9	10	9	18	19	1
4	9	10	10	12	19	22	3
5	9	10	12	12	19	24	5

Table 5.1.: Grip detection. Ground truth based on video recordings and detected number of grips. *LH:* left hand, *RH:* right hand, *V:* video, *S:* sum

Furthermore, the minimum, maximum, and average number of detected holds was calculated for each route. This was done for the whole data corpus. Additionally, the number of holds attached to the wall was included in this analysis. Table 5.2 shows the results. The actual number of holds per route ranged from 16 to 21, while the average detected number of grips Although the average difference between the actual number of holds and the average number of detected grips was 8.0 a correlation could be identified. A computation of the Pearson correlation resulted in 0.788 which shows a significant relation between the detected number of grips and the actual number of holds mounted on the climbing wall. The standard deviations of the average number of detected grips ranged from 2.78 to 4.32.

5.2.2. Route Recognition

To evaluate the route recognition itself, exhaustive and non-exhaustive cross validation methods were applied: *leave-one-out cross-validation* (LOOCV) and *2-fold cross validation.* (2FCV). When applying LOOCV, for every dataset the systems tries to recognize the route based on all 49 remaining recordings. For this, the evaluation script iterates over all recordings and queries the recognition system, which responds with a route id. Since all recordings, including the testing data, are linked

Route	actual no. of holds	min	max	mean	SD
Route 1	16	21	32	27	2.78
Route 2	21	26	39	32	4.30
Route 3	18	21	34	25	4.32
Route 4	16	19	28	22	3.62
Route 5	17	16	31	22	3.60

Table 5.2.: Statistics to the number of detected grips for all routes used in the study. It can be seen, that the number of actual holds correlates with the average number of detected holds per climb.

with the corresponding route, the number of correctly recognized routes can be divided by the number of processed routes. This results in the recognition rate. The results of this validation method should show how good the system works, when a relatively large number of recordings per route is available.

Leave-one-out cross-validation This LOOCV is executed two times with a slightly different training set. In the first run the training set contains all records except the one record which is used for testing. To validate if the recognition is influenced by the fact that the training set and also the testing set both contain records of the same person, the following method was applied. Whenever a dataset was used for testing which was recorded by participant A, all records from this participant were removed from the training set. As a result, this should show whether the recognition system is influenced by user dependence, or if a *general* corpus of foreign training data is sufficient.

Applying the LOOCV over the complete dataset resulted in a recognition rate of 100%. When using only “foreign” training records, i.e. the training dataset does not contain recordings of the user whose dataset is to be recognized, a recognition rate of 100% was achieved.

Two-fold cross-validation To investigate how good the system performs when only a small number of recordings per route is available a 2FCV was applied. In a 2FCV the available data is divided into two groups of the same size. One group is used as training data, while the other one is used for testing. In the case of the recognition system, the datasets can not be simply divided into two parts. This is due to the fact that it could not be assured that every route is equally represented in each group. For this, the two sets (*training* and *testing* data) are compiled as follows. Each route's dataset is shuffled and afterwards split into two parts. These two parts are then appended to the *training* group, respectively the *testing* group. The resulting groups are then analyzed with the 2-fold cross-validation described above. This step was performed 100 times to get a more meaningful result.

As for the LOOCV, the 2FCV is also applied in two modes. In the first run the training dataset was not modified and contained a random set of recordings, except the ones that were used for testing. In the second run, the training dataset was modified as follows. At first, all participants which created records used in the training set were identified. Then, all records which were created by these participants were removed from the testing dataset. This ensured that the recognition was not influenced by user dependent records.

The application of the 2FCV resulted in an average recognition rate of 93.11% ($SD = 5.52$). When observing only foreign training records the average recognition rate was 90.19% ($SD = 5.39$).

5.2.3. One Handed Recognition

Motivated by the growing popularity of smartwatches, the validation methods described above were also applied on a modified implementation of the recognition system. The implementation was modified in such a way, that it would only consider either the left or the right hand for training and recognition. This could be easily achieved since both, the data for the left and the right hand were gathered separately. The current implementation of the climb segmentation, that is, identifying the ascent within a recording, uses the sensor data of both hands. Since the grip detection relies on the correct segmentation of the ascent, an evaluation of the grip detection using only one hand was not performed.

Applying the cross-validation methods on only the left and only the right hand resulted in different recognition rates. The leave-one-out cross-validation scored with 84% for the left hand and 94% for the right hand (see Table 5.3). Using only user independent data sets resulted in recognition rates of 68% and 94%. It can be seen that using only the data from the right hand resulted in a recognition rate almost as good as using both hands.

When applying a 2-fold cross-validation similar observations could be made. Using only data from the left hand resulted in an average recognition rate of 73.15% ($SD = 6.95$) (see Table 5.4). Applying the 2FCV on only data of the right hand resulted in an average recognition rate of 89.46% ($SD = 4.99$). When considering only user independent records recognition rates of 69.19% ($SD = 6.36$) for the left hand and recognition rates of 87.46% ($SD = 5.4$) could be achieved.

	LOOCV		
	Left	***Right***	***Both***
complete	84.0%	94.0%	100%
user independent	68.0%	94.0%	100%

Table 5.3.: Summarized evaluation results of the LOOCV. Using only data of the right hand results in higher recognition rates as when only using data of the left hand.

	2FCV					
	Left		***Right***		***Both***	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
complete	73.15%	6.95	89.46%	4.99	93.11%	5.52
user independent	69.19%	6.36	87.46%	5.40	90.19%	5.39

Table 5.4.: Summarized evaluation results of the 2FCV. As in the LOOCV, only data of the right hand results in higher recognition rates as when only using data of the left hand.

5.3. Discussion

5.3.1. Grip Detection

When analyzing the grip detection performance, it can be seen that randomly picked samples (see Table 5.1) showed good results. The difference between the actual number of attached holds and the number of detected holds is due to the various possible climbing styles. First, a usual technique is to grip a hold with both hands (also known as matching). This is used whenever the next hold is too far away or difficult to grip. Very fast transitions from one hold to another or the movement away and then again back to hold may also result in detection errors. Extensive use of momentum during an ascent may also influence the efficiency of the detection. Another reasons for the varying number of holds is the fact that some climbers do not use every single hold that is available. Additionally, it is also possible to use the wall itself as support, which could be falsely detected as gripping. Also sometimes climbers use a single hold for a really short amount of time, using the momentum to ease the transition to the next hold. All these reasons may lead to a false detection of grips.

This can be also seen when investigating Table 5.2. Although the standard deviation (see Table 5.2) of the average number of detected grips is relatively low, there are sometimes outliers. This can be noticed in the maximum number of detected grips in route 2. When investigating the video recording of the corresponding dataset, it could be seen that the participant struggled a lot during her first ascent. This resulted in changing the grip of her hands multiple times before continuing with the climb. As a result, the system detected more grips than a *normal* ascent would require. An implication of that would be, that the recognition performs good at routes which are climbed confidently, but may fail when the climbers struggles during the ascent.

5.3.2. Route Recognition

When observing the evaluation results suggest that an automatic route recognition based on wrist worn IMUs is possible and operative. The very good recognition rate of 100% when applying the LOOCV may have several reasons. First, a large number of training records per route is available. Whether this would be the case in a productive environment is discussed later on. Additionally, a relatively small number of routes is used. This could be investigated further in the future.

As it can be seen in the difference between the LOOCV and the 2FCV, a larger number of recordings per route is beneficial for the recognition process. When applying the 2FCV on an unfiltered training set, a higher recognition rate than in the other run could be observed. The (filtered) training set used in the second run of the 2FCV used only records from participants which were not included in the testing dataset. The cause for the difference between the runs on the filtered and unfiltered dataset could not be definitely identified. One reason could be the resulting smaller number of training data sets. A small training dataset increases the probability of false recognitions. In future work, a more extensive study could give more insights in this problematic. The second reason would be the difference in climbing styles between the participants which are responsible for the training data sets and the participants which are responsible for the testing data sets. As it can be seen in the high recognition rate of the LOOCV, a higher number of training datasets would solve this problem.

5.3.3. One Handed Route Recognition

Using only one hand for recognition and training resulted in promising insights. It could be observed that when using only data from the right hand, higher scores could be achieved as when only data from the left hand was used. This could be due to the fact that most of the participants were right-handed. Gripping with the dominant hand might result in a more precise movement and in less jitter of the limb. With this, a better recognition of the orientation is achieved and thus, a more expressive sequence of orientations is used for the recognition process. The fact that the LOOCV for only one limb still performs good may be a result of the large number of records per route. This assumption is encouraged when considering the results of the 2FCV for only one limb. Smaller training sets result in lower recognition rates.

The results suggest that in future work the application of smartwatches for route recognition should be investigated in more detail. Using future sports bands that allow access to the raw data could also be used for the recognition and would make special wrist bands for climbing recognition unnecessary.

5.3.4. Prerequisites

Currently the system relies on the assumption that each recording contains exactly one ascend. In the current prototype this is achieved by turning the devices on before the climb, and switching them of after lowering. The ultimate goal would be to integrate a climb segmentation which would recognize each climb within a recording of a complete climbing session. This could be established like described in [21].

Another prerequisite is the existence of a sufficient amount of training data. Initial training data could be assessed by the route setter herself. After setting the new route, she could climb the route a couple of times which would suffice for a basic training data set. Another option would be crowdsourcing. A corresponding smartphone application (see Figure 5.3) could be used to link recordings of the wristbands to the manual logging of climbed routes. To give the users an additional value, the application would not only show the user's climbing diary it could also give training tips based on her climbing history. As motivation for the linking of recordings with routes, an achievement system could be deployed. The user could gain achievements like badges or coupons for free admittance in the climbing gym. Considering the scenario described in Chapter 1, the gym operator would also profit from knowing which routes are being climbed. This would justify the expences of the coupons.

5.3.5. Limitations

The current implementation of the system limits the recognition to routes which were fully climbed, i.e. climbed from the bottom to the top without falling or resting. Routes which are only climbed partially are not recognized, since the system would not find a match to a partial route. This is due to the fact that the edit distance, which is the similarity measure, is also influenced by the different number of recognized grips during two ascents. A comparison between an incomplete route and the training set would result in a higher edit distance per se. Depending on the intended use of the system, e.g. only as list of completed routes in a climbing gym, this might not be flaw. In fact, a common training method for endurance training is to climb a well known, but hard route multiple times [15].

Shaking the arms for relief, fast switching of holds, chalking, or clipping might evoke irritations of the grip detection. This results in too many or too few orientations represented by an ascent. As a result, the edit distances derivates from the actual value. To overcome this issue, machine learning could be applied to recognize and discard non-transition movements like the ones listed above. With this technique grips could be identified better and non-transition movements could be discarded. This would result in a better segmentation, which would give better route recognition rates.

5.4. Conclusion

The analysis of the recognition system showed promising results. Eight participants climbed five routes, resulting in 50 recorded data sets. These datasets were used for a combination of two cross-validation methods. The leave-one-out cross-validation resulted in a recognition rate of 100%. A 2-fold cross-validation was performed 100 times and resulted in a recognition rate of 93.11%. Considering the good performance of the recognition process when using the data of only one limb, the use of smartwatches as tracking device should be investigated in more detail.

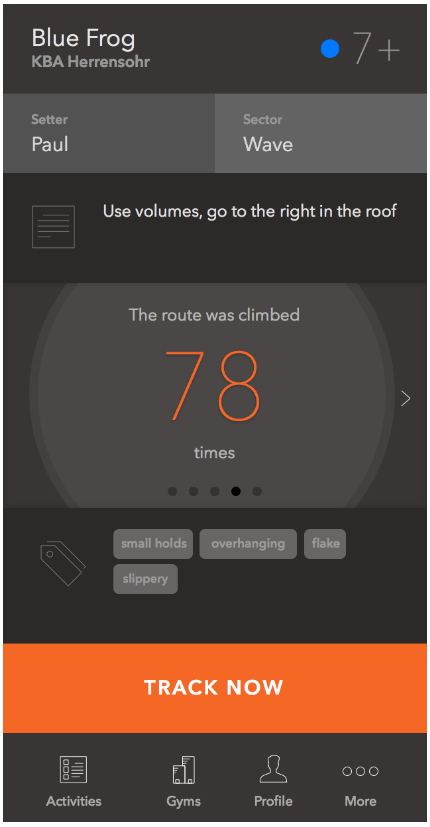


Figure 5.3.: Possible UI for tracking climbing routes.

In general, the recognition could be improved in future work by an extended user study. Furthermore, machine learning methods could be applied to obtain a better grip detection. A better grip detection might also result in a higher recognition rate.

Since the recognition relies on training data, two concepts were introduced to obtain this training records. One option would be, that the setter of the route could climb the route a couple of times, while wearing the wristbands. As an alternative, the training sets could be compiled through crowd sourcing. Climbers could wear the wristbands and link recording with routes with the help of a smartphone application. Incentives for the use of the application could be given by virtual achievements or coupons for drinks.

6. Conclusion and Future Work

The goal of this thesis was to develop an automatic route recognition system based on wrist-worn IMUs. This chapter concludes the findings that were achieved during the development of this thesis and points out the resulting contributions. Furthermore, it presents ideas and suggestions for future work.

6.1. Conclusion

In this thesis, a method was proposed which recognizes routes a climber performs during a climbing session, using wrist worn IMUs. Although the user would not need to interact with the devices, the system would recognize the route which was climbed based on the sensor readings. The implemented method was evaluated and a recognition rate of 93.11% could be achieved. This shows that the proposed method is operative.

Motivated by the concepts of Quantified Self, a self-contained concept for climbing gyms based on automatic route tracking is proposed. Based on a scenario, several benefits are shown which would arise from tracking every route a climber is performing during a climbing sessions. These benefits are not only valid for the climber herself, but would also apply to the climbing gym operator. While the use of the data does not necessarily comply with the Quantified Self idea, the outcome of continuous tracking of climbed routes can be used in several ways. The climber would get an extensive summary about her training progress while the gym operator gains insight about the usage of the climbing routes.

Several studies are presented which investigate the motivation behind activity tracking and the used methods. Furthermore, the similarities between the Quantified-Selfers and the other people are shown. Customer ready tracking devices like the fitbit or the Nike+ Fuel Band enable everyone to track certain aspects of their lives. This ranges from tracking of sport activities through step counters to sleep cycle analysis. While such devices cover sports like running and cycling, climbing did not find much attention in HCI research. Several activity tracking related research topics are introduced and followed by topics to HCI and climbing. Based on the findings explained in the related research topics, requirements for the automatic route recognition could be inferred. Body worn sensors, like those used in the *ClimbAX* system [21], have shown that climbing skill assessment using accelerometer data is not only possible but also reliable.

A preliminary study investigated the use of activity or sports trackers in the climbing community. For this, 92 participants were asked to answer questions in an online questionnaire that was distributed in several Facebook climbing groups.

The questionnaire contained questions about the participant's climbing habits, if the participant is tracking sports, if she records her climbing history and if so, which technique she used. The results split the group in two parts. One group tracked sports and other activities while the other did not. The groups had roughly the same sizes. Interestingly, some participants out of the *non-tracking group* stated that they would nevertheless note down routes they climbed. A common reason against tracking of climbed routes was that it would be too cumbersome. Furthermore, some climbers stated that they would rather concentrate on climbing but would also be interested in their quantified climbing progress. Based on the insights of the study and the feedback from the participants, requirements for the automatic tracking system could be assessed.

The automatic climb recognition system is based on the assumption that a route can be characterized by the several arm orientations which arise during an ascent of a route. Movements are distinguished from grips by applying filters and thresholds. Whenever a hand touches a hold, the system logs the orientation of the corresponding arm with the help of wrist worn IMUs. The resulting orientation sequences of both arms are used as part of a characterization of the route. Multiple recordings per route are used as training data for the recognition. New, unrecognized recordings are compared to the training datasets with the help of a weighted edit distance. The sequences of the routes are treated as strings of symbols (the symbols being the different orientations) and are compared with a weighted Levenshtein distance. Every new recording is compared with the training data and the match with the smallest edit distance is chosen as the resulting route.

A final evaluation showed that the climb recognition system is working. For the evaluation, eight participants were asked to climb five routes in a local climbing gym. In total, 50datasets could be assessed which were then used to evaluate the implementation. Two cross-validation methods were applied: *leave-one-out cross-validation* (LOOCV) and *2-fold cross validation* (2FCV). This resulted in a relatively high recognition rates: For the LOOCV a recognition rate of 100% could be achieved while the 2FCV scored with 93.11% ($SD = 5.52$). To further improve the recognition rates, machine learning methods could be used to distinguish between transition movements from one hold to another and arm movements like chalking, clipping the rope in a carabiner or shaking for relief. The evaluation of the system showed that an automatic recognition of climbing routes using wrist-worn IMUs is not only possible but also operative.

6.1.1. Contribution

The automatic assessment of climbed routes contributes to several aspects of the climbing sport. First, the assessed data could be used in climbing training. A climbing coach could get an overview of climbed routes of her trainee and could modify the training plan accordingly. Climbers without a personal coach could use the assessed data within a smartphone application. She would have access to real time performance monitoring and could get insights into her climbing skill progress.

Climbing gym operators could get statistics about the use of the gym's climbing routes. With this knowledge they could detect and optimize flaws in the route setup. This would result in a better distribution of climbers within the gym, thus resulting in more customers.

Finally, the automatic assessment of climbed routes could be used in a rehabilitation program. After an injury a system could recommend, based on her climbing history, routes that are easier as her usual climbing skill level. After a certain amount of routes the system could advise her to stop to prevent losing the rehabilitation effect.

6.2. Future Work

Although the results of the evaluation are satisfying, there are aspects that need more attention in future works. First, a larger number of routes has to be included in the evaluation. This would give insights into how well the system scales. With an increasing number of routes, the detection of movements and grips has to be refined. Currently the system does not distinguish between transitions from one hold to another and other movements like clipping, shaking the arms for relief or chalking. These movements could be detected using machine learning methods.

To get closer to the goal of making this system consumer ready, a climb segmentation as in [21] would have to be included. Currently the system relies on the assumption that every recording contains one single ascent of a route. Furthermore the system only detects complete ascents of a route. Falls or resting on the rope will lead to false results. Only partially climbed routes will also result in recognition failures.

Additionally, a definite method has to be developed to collect initial training data for the recognition. A possible solution would be a corresponding smartphone application that would allow the route setter to record a couple of training dataset. Another option would be crowdsourcing. With the help of a smartphone application, every climber could link the recordings after every ascent of a specific route. As a motivation, gamification methods could be used. Since the climbing data is not only beneficial to the climber herself but also from commercial interest of the climbing gym operator, coupons for free admittance or drinks could be given away to motivate the climbers to link routes with recordings.

Including performance assessment into the system would make it possible to detect user problems that arise at specific routes. These problems could be deducted by the stability and power the user shows during an ascent. With the help of these data and the knowledge of available routes, the system could make suggestions that would tackle the climber's weaknesses and helps her to improve her climbing skills.

Another way of extending the system would be the implementation of a real-time recognition. Currently the user would have to upload the data into the online portal to receive the results of her climbing session. A real-time recognition could be achieved by using Bluetooth-Low-Energy modules within the sensors which could transmit the collected data from the wrist-worn sensors to the user's smartphone after every ascent. With the immediate knowledge about the already climbed routes a virtual climbing coach could adapt to the user and suggest routes which fit into the current state of training. This would be especially helpful for smartwatches. In fact, smartwatches or wrist-worn activity trackers could replace special sensors like the ones used in this thesis. This is shown by the promising results of the one handed route recognition evaluation.

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A. Appendix

A.1. Algorithms

Algorithm 1 Route Distance

```
procedure RouteDistance(a, b)                          ▷ Dataset a and b
    sum ← Levenshtein(a.left_sequence, b.left_sequence)
    sum ← sum + Levenshtein(a.right_sequence, b.right_sequence)
    return sum
end procedure
```

Algorithm 2 Route Recognition

```
procedure RecognizeRoute(new_dataset, training_datasets)
    smallest_distance ← INT_MAX
    nearest_dataset ← None
    for all t_set in training_datasets do
        current_distance ← RouteDistance(new_dataset, t_set)
        if current_distance < smallest_distance then
            smallest_distance ← current_distance
            nearest_dataset ← t_set
        end if
    end for
    return (nearest_dataset.route, smallest_distance)
end procedure
```

Algorithm 3 Angle Distance

```
procedure AngleDistance(a, b)
    d ← a − b
    d ← ((a + 180) mod 360) − 180
    return abs(d)
end procedure
```

Algorithm 4 SymbolDistance

procedure SYMBOLDISTANCE(a, b)
    $s \leftarrow 0$
    for $i \leftarrow 0, 2$ **do**
        $s \leftarrow s + AngleDistance(a_i, b_i)$
    end for
    return s
end procedure

A.2. Questionnaire

The following questions were asked in the prestudy which is described in chapter 3 on page 21.

1. Personal Questions
   a) Age
   b) Sex
2. General Questions to Climbing and Bouldering
   a) In which grade do you climb?
   b) In which grade do you boulder?
   c) For how many years do you climb?
   d) Where do you go for climbing? (1=outside, 10=inside)
   e) For how many years do you boulder?
   f) Where do you go for bouldering? (1=outside, 10=inside)
3. General Questions to Sports Tracking
   a) Do you use an activity tracker device?
   b) If no, why not?
   c) If yes, which devices do you use?
   d) Do you use an activity tracker smartphone application?
   e) If no, why not?
   f) If yes, which applications do you use?
   g) Which activities do you track?
   h) Do you use an online portal to manage your activities?
4. Questions to Sports Tracking and Climbing
   a) Do you record which routes or problems you climbed?
   b) If no, why not?
   c) If yes, how do you do that?
   d) Would you use a system which automatically tracks the routes you climbed?
   e) If no, why not?
   f) If the system would not be able to operate fully automatically, what user interaction would be acceptable?

5. Final Questions
    a) Which assessment would be more important for you? (1=Which routes I climb, 10=How I climb)
    b) Do you have ideas who technology could be used to enhance climbing?

A.3. DVD

The contents of the DVD are structured as follows:

```
-- ClimbSense         // Django Installation and Data Importer
-- Thesis             // This document
-- SensorBox          // OpenScad Files, Firmware, and Setup Instructions
```