Climber Behavior Modeling and Recommendation

Iustina Ivanova
Free University of Bozen-Bolzano
Bolzano, Italy
iivanova@unibz.it

ABSTRACT

Sport climbing is becoming more and more popular, even among non-specialists. While new routes are built each year, both indoor and outdoor, there is no effective tool for supporting climbers to choose the most appropriate routes, either for training or simply enjoying. Route recommendation is hard and risky because a reliable evaluation of the climber's capabilities, status and subjective difficulty perception is necessary. This can be achieved only with the exploitation of Internet of Things (IoT) sensors for the automatic recording of climbers' activity. In this research, we want to further extend the still young research subject of activity recognition in sport climbing and combine this with new recommender systems (RSs) techniques for route suggestion. We have developed an initial solution for unobtrusively and automatically detecting climbers' activities in a gym, and we are now connecting this information with the manual inserted diary data of climbers by means of a mobile application. We present the design and the open research questions for a system that leverages sensor data and explicit feedback to generate a climber's profile and recommend suitable routes.

CCS CONCEPTS

• **Information systems** → *Recommender systems*; **Personalization**; • **Hardware** → Sensor applications and deployments.

KEYWORDS

user modeling, recommender systems, activity recognition, IMU sensors for climbers, sport analytic, climbing routes suggestion, climbing route grades prediction

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1 RESEARCH PROBLEM

Sport climbing was established as a sport in the 19th century as a training activity for alpinists [2]. Northern England and the Italian Dolomites are among the sites where the first climbers gathered to climb and explored the mountains. At present, sport climbing is widely enjoyed both as a leisure activity and competitive sport, which led to its inclusion in the 2021 Olympics. Similarly to other sports, sport climbers have shown interest in novel technologies that would allow them to keep track of climbed routes and even facilitate the design of climbing programs for training. One notable tool on the market to support climbers is a climbing app developed by the Vertical-Life company[1] situated in South Tyrol. It supports climbers in their daily climbing activities: users manually insert information about the routes which they climbed. As a result, the app serves as a diary for training activities, which is an important tool for climbers who would like to train more efficiently [8]. Currently, the functionality of this application, like other similar ones, does not provide route recommendations to the climbers, although they often face such a problem: choosing the most suitable routes among the large set of those that are available (e.g., nearby). Climbers have their own specific goals: some athletes are interested in routes of a defined level as part of their training goals, some of them are more interested in enjoyable and fun routes, while others prefer long alpine routes. However, the design of an effective Recommender System (RS) for climbers has not been systematically explored. Ricci et al. in [35] built a travel RS, where sport-climbing is included as part of recommendations, but without being able to generate specified suggestions for routes that may satisfy the above-mentioned users' requests. As a matter of fact, there is no RS for climbers, while there are several relatively small and simple public projects on the GitHub platform, which addresses the basic task of climbing routes in the USA [3, 6, 9, 29, 38]. Most of them are for outdoor climbing routes and are based on a small sample of climbing routes and regions of the US, focusing on the simple task to predict the climber's rating for a new route. The main limitation of the existing research projects is that they do not provide an effective solution to the identification of "suitable" recommendations, where "suitable" is defined above. They are actually not solving any real problem of climbers.

In order to address the indicated shortcomings, we propose a research program aimed at modeling the users and the items with specific features that capture important knowledge useful to make recommendations for climbers. Moreover, it is generally acknowledged that effective recommendations can only be made by exploiting reliable (personal) information, and such information comes from either explicit or implicit feedback of the user [23]. In our target scenario, explicit feedback is given by users by manually inserting information about themselves, their activity and their preferences. This information, for instance, is actually (very partially) present in the dataset collected by the Vertical-Life application: climbers indicate their performance in specified routes; how they perceive the route difficulty after climbing the route; subjective rating of a route and other information related to the climber status and activity. Such feedback shows a climber's subjective evaluation of the

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[1] https://www.vertical-life.info/

experienced routes, up to the specified time point, the physical ability of the sportsman, and what type of routes they usually like and dislike. However, explicit feedback is always partial since climbers, as with many other users of similar "diary" applications, will never report all their activities. Hence, in addition to explicit feedback from the mobile application, we are developing specific techniques aimed at collecting more data and, therefore, improving the quality of the user's profile. We aim at collecting more "implicit feedback" by using Internet of Things (IoT) sensors, attached to the climbing devices. For instance, in this context, 'Vertical-Life' company developed a sensor called 'smart quickdraw' in 2019, which has the potential to unobtrusively collect climbers' data for the analyses of daily climbing activities in a gym [18]. The sensor is, in short, an acceleration sensor placed into a box attached to the strip of a standard quickdraw. In fact, it is very important to have a reliable flow of climber's activity data by means of sensors, as this data can be used to derive information about the training activity and skill level of a climber. Thus, automatic activity and performance recognition is the first step to derive important "implicit feedback" and is extremely useful for climber profiling.

Hence, our research project focuses on a scenario where activity detection and monitoring is used in order to profile the users automatically via sensor analysis, identify their preferences and physical levels, and build an RS, which would suggest to the user the easiest, enjoyable and safe routes. A secondary goal of our research is to enforce safety in the gym by automatically detecting risky behaviors.

2 RELATED WORK

This section, firstly, provides a brief overview of activity recognition techniques that have been explored in the literature and what sensors are employed for tackling this problem. Inertial sensors, such as accelerometers, gyroscopes, and magnetometers, are the most commonly used device to capture information related to climbers activity. Fewer works have considered video-based approaches [37]. Some of the challenges that need to be faced when working with sensors as data sources will be further discussed. The second part of the section deals with state-of-the-art RSs in the climbing domain, and in particular, those providing route recommendations.

2.1 Activity recognition

Automatic recognition of human *activities* is an important and challenging topic in many application domains. It aims at determining the activities of a person or a group of people based on observation data and knowledge about the context in which activities occur [34]. Activities in rock climbing have several definitions in the literature, leading to misunderstandings about these concepts. We will define activity as movements of a person at some moment. On the one hand, most of the articles are dealing with solutions where sensors are positioned on the body of the climber: for example, Kosmalla et al. in [24] and Ladha et al. in [25] employed wrist-worn inertia measurement units (IMUs) to distinguish climbing from background activities. Five IMUs sensors are placed on the bodies of climbers by Seifert et al. in [39] to identify clusters of the patterns that represent the movements. The same number of IMUs is employed by Boulanger et al. in [5] to detect a specific set of activities in climbing. In this work, climbing activity is seen as composed of: postural regulation, hold interaction, traction, and immobility, which are in turn composed of movements of limb and trunk. Four sensors are used in [14] by Ebert et al. to identify climbing activity and segment it into transition and rest period. On the other hand, some researchers placed sensors on climbing equipment. For instance, in [4, 44], Tonoli et al. and Bonfitto et al. showed that the IMUs sensor on the harness could be used for fall detection, where the harness is defined as an element of climbing and mountaineering equipment that the athlete puts on and attaches themselves to the climbing rope with a knot. The main limitation of the above studies is that they have used body-worn sensors, which are not convenient and are not typically accepted by climbers, whereas in our system we would like to use contactless sensors, such as 'smart quickdraw'; furthermore, the described methods are not employed for lead climbing, but instead, for top-roping or bouldering, and we would like to address this limitation. In addition to the sensor-derived data, there are research works that employed video cameras. Cordier et al. in [10] identified the activity of *route finding* with a video camera and light-emitting diodes attached to a climber during their climbing. Another research on activity recognition by video cameras is done by Kajastila et al. in [20, 21], where the authors detected the activity of *hold gripping* via projected light on the wall and Kinect depth camera. However, all the video-based systems have severe limitations connected with privacy, as climbers hardly accept filming during their activities and legally enforceable rules.

Some additional research work focused on climbers' skills analysis and profiling. Rather simple techniques were used to group climbers based on their level and predict the performance of a group [11, 13] or a climber [12]. But that prediction was not then used to generate suggestions for finding the next routes to try. Profiling of a climber is also done in [28], where seven variables were used to assess an athlete's skills, but, again, the authors did not employ this information for supporting the climber's decision-making. In addition to skills assessment, there is another complex problem to consider, namely, route difficulty identification. This problem was introduced by Phillips et al. in [32], who developed a language for a route description to support *route setters*, or experienced climbers, who place holds on the wall with designated start and finish holds in order to build a 'route' or 'problem'.

2.2 Recommender systems for climbing routes

RSs have been applied in many websites, and their main task is to help the user make a decision or remain informed about a topic [36]. Nowadays, for instance, streaming platform companies, have a huge selection of products that creates a problem of information overloads in their customers. RSs address such a problem by personalized suggestions of products to customers [30]. In sports, RSs have emerged relatively recently: this is due especially because of the development of IoT sensors and their affordability: for instance, the Movesense sensor, which is used for various applications in the sport domain [31, 41]. One notable example of the use of RSs in sports is the application developed for runners by Berndsen et al. in [1], where the authors use collaborative filtering (CF) to support beginners in marathon preparation: they suggest training plans and race strategies to beginners by exploiting data collected from sensors during marathon running. The method is developed further in [42], where the authors applied CF to help marathon runners obtain their best performance in the next race by suggesting a suitable tailored pacing plan. A similar technique is also applied in [43], where the system predicts the performance of the athletes in ice-skating racing based on the historical information collected by IoT sensors and by using a user-based nearest neighbors approach. Some research work also focused on routine training recommendations. In [15], Feely et al. created training plan suggestions for marathon runners from their implicit feedback collected via IoT runner sensors during their preparation for the marathon race. They profiled athletes with physical conditions from their training progress at a specified time, predicted the race time, and suggested the training plan based on the specific weaknesses of the athlete. In another work [33], Pilloni et al. developed an RS for coaches who are interested in the identification of loosening motivation of the athletes: they profiled users with smartphone sensors, which store information of their activity and calculate performance. The main limitation of the outlined works is that they collected a large amount of sensor data capable of producing reliable RSs: however, in climbing, good quality data is not available yet.

There are also some simpler RSs based on search tools, where the user manually inserts the desired characteristics of a route and obtains matching recommendations. For instance, in [27], the authors describe the RUNNERFUL application, where the user can obtain running route recommendations based on the entered parameters. A similar solution was developed by Vias et al. [45] in an RS for hiking routes in the southern Spain region, where they consider specific search criteria, time complexity for the route, and aims at distributing hikers in the region. Another RS, in a related domain (hiking trails in Switzerland), was described by Calbimonte et al. in [7], where they profile users with a questionnaire and suggest routes matching the user's physical, technical and psychological capability. The main limitation of these works is that they require explicit feedback of the users in order to profile them and they do not consider the usage of sensors.

As we can see, the use of RSs techniques for sports activities, and climbing routes recommendation, in particular, is at an early stage of development. All current solutions are related to predicting traces that athletes would like, and they are mostly related to different domains rather than climbing. Nevertheless, some publicly available projects indicate strong interest in this problem: for example, Viet Nguen in [29] described a CF recommendation engine for climbers using data scraped from mountainProject.com. The system predicts the climber's rating of a route from the Red Rocks Canyon climbing area (US), and is based on k-Nearest Neighbor and uses cosine similarity. A similar project is presented by Brochard in [6], where the author predicts how much the user would like a route on the scale from 1 to 4, where the dataset for this project is also taken from mountain.com. User-based CF was implemented in the project of Colley in [9] on the dataset, which is collected from the 8a.nu website.

Analyzing state of the art, we conclude that, in general, sport-related RSs are now studied and can enter into the practice of various sports. However, the specific applications of RSs to rock-climbing have not yet been considered, even though many climbers would be interesting in the suggestion for routes to climb next.

3 RESEARCH QUESTIONS AND PROPOSED APPROACH

Considering the aforementioned research gaps, the overall goal of this thesis project is *to model climbers, routes, and route setters in order to generate personalized recommendations for climbers about what route would be suitable for them.* In addressing this goal, we would like to obtain as much information as possible from implicit feedback (sensor data), and secondarily from the user (explicit feedback). However, the state of the art of techniques for sensor data analysis in the climbing domain is in the early stage, especially for sensors embedded in the climbing environment. Hence, we need to implement reliable techniques that enable us to recognize the climber's activities automatically. Then, we would like to combine this information extracted from sensor data with information coming from user explicit input in a mobile application. This generates a historical database of climbers' activities that can be used to extract their preferences and abilities.

In particular, our approach relies on the modeling of the three above-mentioned entities by means of two types of information: IoT sensed data collected by sensors embedded in the climbing environment and climbers' explicit input. We will develop a sensing platform and analysis framework for tracking climber's activities and assessing climbing performance during training. Then, in collaboration with a company offering various types of services to climbers, we have the possibility to acquire contextual information, information about the overall user's climbing abilities, and user feedback. The first research question is related to activity recognition as follows:

- **RQ1.** How to design an activity recognition system based on IoT sensors embedded in the climbing environment to automatically recognize the activities performed by the climbers?

For answering the research question mentioned above, we follow the definition of climbers' activities proposed by Boulanger et al. in [5], but we extend their catalog. For instance, in the first part of our research, we have focused on 'rope pulling', namely, the activity in lead climbing which happens after the 'ascent', when the 'lowered' activity is finished. The recognition of 'rope pulling' is important because it is relatively easy to detect, with the available sensor, and can be used to segment climbing sessions in the flow of data collected by the sensor embedded in the climbing environment. To collect even larger labeled datasets and, hence, to improve the accuracy of the algorithm, we designed methods that simplify and automate the tagging task (assign a window of data samples to an activity).

The second question is related to performance analyses of climbers:

- **RQ2.** Can such an activity recognition system help in identifying climber's capabilities, e.g., by detecting falls, climbing speed and fluency?

A preliminary analysis has shown that it is possible to cluster climbers based on their skills by exploiting the sensors' data [19]. The proposed method is explained in section 4.2.

Finally, as mentioned before, explicit feedback is information manually provided by climbers about their sports activities. In [16], Hörst describes the objective evaluation of a climber's performance, which can be described as identifying personal weaknesses through self-investigation and coach feedback. Hence, with this manually inserted information, one can analyze the performance of a person. Accordingly, we would like to answer the following research question:

- **RQ3.** Can the climber's feedback and activity recognition help in creating an RS for route suggestion tailored to the climber's preferences and capabilities?

The outlined research questions have been initially addressed in a case study, where both sensor data (implicit feedback) and explicit climber feedback on performed activities collected by mobile application for climbers used by around 300,000 registered users, have been exploited but not yet combined. The sensor data is collected during our experiments and will be routinely collected by the gym owner. We consider activity recognition via quickdraw sensors in indoor gyms, and for outdoor climbing, body-worn sensors will be employed in the future. Furthermore, to identify a person with the target sensor, we develop a system with QR code scan with the phone.

4 PROGRESS TO DATE AND FUTURE WORK

4.1 Climber activity recognition via IMU sensors

As previously stated, it is important to automatically detect climber's activities, by using reliable sensing technologies; this information can be used for profiling climbers, route setters, and routes. Previous studies have employed body-worn sensors for such purposes, but rarely sensors placed on the climbing wall, thus having essentially no impact on climbers' approach to the sports practice. We have conducted several experiments aimed at testing which climbers' activities can be recognized from the data acquired by sensors embedded in the environment. In [19], we show that the activity of 'rope pulling', which indicates the end of a complete lead climbing activity, can be detected using data generated by a standard quickdraw enhanced with an accelerometer (i.e., 'smart quickdraw') placed on the second-lowest position from the ground. The data is processed with a sliding window method, a common technique used for human activity recognition from sensor data [17]. We created a binary classification problem for each window, where class 1 is "rope pulling", and class 0 is "not rope pulling". As in [25], we generated 60 features for every window and compared the performance of several machine learning models to solve this classification task. We varied the number of strides between windows in order to find the best performing one, i.e., with the best accuracy in identifying the exact time interval of the rope pulling activity. As a measure of performance, we used the Jaccard index (JI), which represents the ratio between the size of the intersection of the actual and predicted rope pulling segments and their union size. Overall, the experiments resulted in the detection of 16 out of 17 rope pulling activities, with an average JI of 0.93 (1 indicates perfect overlap).

As an additional step, we tried to profile climbers based on two features derived from the acceleration signals: duration of ascent and the cumulative motion magnitude of the sensor-enhanced quickdraw during a climb per unit of time. We observed two clearly separated clusters of climbs in the 2-dimensional space corresponding to each of the climbers. From this, we concluded that the style of the climber could be captured by the two features derived from the quickdraw signals.

In a related study, we proposed two approaches to label the 'rope pulling' activity using video recordings of climbs. In the first approach (hybrid method), we combined video and sensor data to detect 'rope pulling' in two computational steps. Firstly, we used video processing and applied transfer learning on RetinaNet [26] to identify the 'lowered' activity, which happens before 'rope pulling'. Secondly, we utilized the sliding windows technique to identify the start and the end of 'rope pulling' in the acceleration data generated by the quickdraw. In the second approach, which is entirely video-based, we used computer vision techniques to detect the sensor-enhanced quickdraw on the climbing wall. Applying transfer learning to Convolutional Neural Networks for object detection proved to be an effective solution for such a task (see [40] for other applications). In this second approach, the 'rope pulling' activity ends when the target quickdraw object is detected without a rope inside, while the start of this activity is roughly estimated by assuming that all rope pulling activities have the same (average) duration. To summarize, both approaches resulted in good identifications of the rope pulling activity on the testing data: we used the same JI metrics for evaluation. The evaluation resulted in recognition rates of 91% for the hybrid and 76% for the video-based approach, respectively.

4.2 Subjective route grade prediction

We have performed preliminary experiments aimed at predicting the subjective evaluation of the difficulty of a route given by a climber. In fact, the mobile application distributed by Vertical-Life allows climbers to insert information about the routes that they attempt. In particular, a climber can insert the date of the particular ascents, the number of attempts, rate the route (number of stars from 1 to 5, where the number of stars indicated how much the climber liked the route), evaluate the style required to climb that route (used by the climber), as well as the perceived difficulty of the route. Route difficulty is measured on a specific scale and it is given by the route setter usually. But, each climber may have, and actually often has, a different perception, hence would give the route a different grade, thus, the realistic grade of a route is a combined evaluation of route setters and users who try it. The prediction of these personal route evaluations is important for computing a reliable and safe recommendation for routes. In fact, the RS should recommend routes that are "perceived" by the climber with a particular difficulty, rather than relying on the subjective evaluation of the setter. This prediction is not an easy task to solve, as it has been shown by Kempen in [22]. It actually depends on many factors, but most importantly: 1) the physical level and skills of the climber; 2) the style of the route (e.g., bouldering style is considered to be harder than lead climbing).

Those factors are analyzed, together with the information of the route setter grade given to a target route in order to predict the climber's subjective evaluation of route difficulty. As an initial step, we have experimented two approaches. The first one is based on machine learning (ML) and uses well-engineered features of the route and the climber for building a predictive model for the regression-based problem. The second one is a standard RS based on Collaborative Filtering (CF) and Matrix Factorization (MF). In the first approach, we create several features, which could capture the most important information that can be used to predict how the route difficulty evaluation of a climber deviates from the route setter evaluation. These features model the skills of the climber and the specific climber tendency to deviate from the route setter evaluation for certain types of routes. In the second approach, we implemented a simple hypothesis that climbers that climb the same routes as a target climber and evaluate them similarly, would also grade the target route similarly.

The initial results have shown that the ML approach is more accurate than CF. This means that some of the climber and route features (user and route profile) that we have identified are indeed correlated with the climber's perception of the difficulty grade of a route. Specific RS techniques, while generally applicable, must instead be carefully tuned to our application. In the future, we will make other experiments using additional information that describes both the climber and the route.

4.3 Future work

In conclusion, we have shown initial results that support the research hypothesis that the considered sensor (smart quickdraw) can be used for activity recognition, climber's skills assessment, and therefore for establishing a connection between explicit feedback collected from the climbers, with sensors' data generated implicit feedback. However, we need to further develop an automatic system that ideally would be able to identify a person in a climbing gym, detect what type of activities they perform, and measure their performance on a specific route. Moreover, our initial attempt to predict the perceived difficulty of a route has shown the importance of better understanding the specific factors that make a route difficult for a climber.

In the rest of this PhD project, we would like to design and evaluate an RS for route suggestion by using both CF and an MF approach capable of extracting informative features of the climber preferences and capability. Hence, we aim at designing a better user profile based on the fusion of sensor data and explicit routes' evaluation. Therefore, additional work is required to connect each user with the available sensors in order to automatically match climbers to sensor data acquired by the infrastructure, and use activity recognition for the better profiling of the climber and improving the recommendations.

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