# Climbing Activity Recognition and Measurement with Sensor Data Analysis

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## ABSTRACT

The automatic detection of climbers' activities can be the basis of software systems able to support trainers to assess the climber performance and to define more effective training programs. We propose an initial building block of such a system, for the unobtrusive identification of the activity of someone pulling a rope after finishing the ascent. We use a novel type of quickdraw, augmented with a tri-axial accelerometer sensor. The acceleration data generated by the quickdraw during the climbs are used by a Machine Learning classifier for detecting the rope pulling activity. The obtained results show that this activity can be detected automatically with high accuracy, particularly by a Random Forest classifier. Moreover, we show that data acquired by the quickdraw sensor, as well as the detected rope pulling, can also be used to benchmark climbers.

## CCS CONCEPTS

• **Human-centered computing → Ubiquitous computing**; • **Computing methodologies → Machine learning**.

## KEYWORDS

Sports analysis; Sensors; Climbing; Activity Recognition

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## 1 INTRODUCTION

In recent years, climbing has become a popular recreational and competitive sport worldwide [1, 2], producing a growing interest in the development of innovative software solutions that could support the training of both professional and amateur climbers. Professional climbers follow rigorous training programs designed by climbing coaches. A coach assesses the climber during a climbing session by observation and then provides feedback by pointing to the weaknesses in their technique and suggesting appropriate training routes. Coaching is also desirable at amateur level; however, due to the large number of climbing enthusiasts, this service cannot practically be provided to each climber in indoor climbing gyms. Automatic or semi-automatic climbing assessment systems have the potential to support professional coaches, and to make coaching more widely available.

In order to implement such training software solutions, one should be able to automatically detect and classify climbing activities and actions (e.g., a fall). We are developing practical and user acceptable solutions for that by exploiting the Internet of Things (IoT) and Artificial Intelligence (AI). We aim at leveraging standard climbing equipment and novel sensing technologies for unobtrusive climbing activity recognition and performance assessment.

We present here the results of some field experiments that demonstrate the potential of our approach. We have used a standard piece of climbing equipment, namely a quickdraw, augmented with a 3-axial accelerometer sensor. This "Smart QuickDraw" is being developed in collaboration with Vertical-Life Climbing[1]. The experiments were carried out at the Salewa Cube[2] and Vertikale[3] climbing gyms, and involved two of the authors of this paper. The specific goal that we consider in this article is the detection of climbing episodes from a continuous stream of accelerometry data obtained from the quickdraw movements. While climbing episodes detection can be easily addressed by asking explicit climber feedback (e.g., by using a custom-designed app or by instrumenting the climbing wall with physical buttons), we are interested in developing solutions that are as unobtrusive as possible. Hence, we have developed a Machine Learning (ML) solution for detecting a particular type of climber's activity, namely the *rope pulling*, which happens at the end of a climb. Our solution relies only on the analysis of the data generated by smart quickdraws. We have compared some ML techniques, and our findings support the hypothesis that acceleration data collected by the sensors attached to quickdraws can be used


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[1]https://www.vertical-life.info/de/gym
[2]http://www.salewa-cube.com/en/
[3]https://www.vertikale.it/

to efficiently and automatically recognize activities performed by climbers, and in particular, the act of pulling the rope. Our results demonstrate the superior performance of a Random Forest classifier that can detect almost all the target rope pulling activities present in the test data. Moreover, we show that the data acquired by the quickdraw sensor and the result of the rope pulling detection process can also be used to provide insights into the fluency of the climbing (i.e., smoothness of the hip trajectory).

## 2 RELATED WORK

Only a handful of studies attempted to design systems for automatic detection and classification of climbing activities and assessment of climbing performance. In this section, we review relevant studies, focusing on the usage of devices for activity sensing and on ML techniques for the detection of relevant activities from sensors' measurements.

Previously published approaches deal with automatic detection of the following climbers activities/actions: falling, gripping the hold, traction, postural regulation, immobility and hold interaction. The raw data related to these activities are generally recorded using wearable accelerometer sensors placed on the climber's body. These sensors generate tri-axial acceleration signals when the climber moves the respective body part. The research method in [8, 10] requires a climber to wear a pair of accelerometers on wrists, the approach in [5] involves additionally the placement of accelerometers on climber's legs and pelvis. A less invasive approach is proposed in [11], where a single accelerometer is placed on the climber's ear. In another work [4], an accelerometer and a barometric altimeter are placed on a climbing harness. In [13], the climbers carried an inertial measurement unit on their hip and the unit was used to evaluate their climbing fluency. It is worth mentioning that several preliminary studies (e.g., [7, 9, 14]) proposed video camera-based activity tracking systems, which, although promising, are not suitable for indoor climbing settings due to the occlusion problem.

Climbing activity recognition is typically modeled as a supervised classification problem for which the sensor-recorded training data is obtained via experiments involving climbers performing specified activities. Generally, the classification is performed not on raw sensor data but, instead, on feature vectors extracted from raw data. In the case of acceleration signals, classification performance can be further tuned by removing the low-frequency component, which is mainly tied to the terrestrial gravity [3]. Previous studies utilized statistical models [5], logistic regression and Restricted Boltzmann Machines [10], or Random Forest, Support Vector Machine, and Naive Bayes classifier [6]. Some research [4, 6] reported promising results of convolutional neural networks.

The objective of our study differs from the mentioned studies as the activity we focus on, i.e., *rope pulling* has not been studied yet. With a view on practical deployment, we utilize sensors embedded in the climbing equipment (quickdraw), unlike previous approaches that require the climber to wear sensors on their body.

## 3 CASE STUDY: ROPE PULLING DETECTION

In sport climbing, the climber relies on fixed bolt anchors that are attached to the wall for protection. A particular piece of equipment, the quickdraw, is clipped to each bolt on one side, while the other side serves the purpose of holding the climbing rope. Quickdraws are typically lined up into a straight series, and are usually shared between multiple routes. A route is a climbing path composed of single-color holds, which the climber must use exclusively during the ascent. Finally, a configuration of several routes that share the same quickdraws constitutes a line. Our case study is dealing with lead climbing, where the climber, while ascending the route, periodically clips the rope through the quickdraws for safety, causing them to move according to her/his actions. The act of pulling the rope to remove it at the end of the climb is at the center of our attention.

An overview of the designed system for rope pulling detection and climbing fluency assessment is shown in Figure 1. Quickdraw movements are captured using a small accelerometer sensor attached to the strip in the central part of the quickdraw. This is a Movesense[4] sensor that is configured to sample tri-axial acceleration data at 50Hz frequency, i.e., one sample every 20ms. Such a sampling rate provides sufficiently detailed movement information, considering that the human movement range is between 0.2Hz and 20Hz. An iPhone X, running the "Movesense Showcase" mobile app[5] and connected to the accelerometer by Bluetooth, is used to record sensor readings. With a view on practical deployment, we adopted an approach based on a unique sensor-enhanced quickdraw, placed on the second-lowest position from the ground.

The full process of rope pulling recognition (see Figure 2) consists of five steps. Firstly, the acceleration generated by the quickdraw movement is separated from the acceleration due to gravity using a low pass filtering technique [3]. In the following step, the full sensor data time series is partitioned into shorter overlapping intervals of sensor data (windows of a few seconds of data). A feature vector for each data window is then built by aggregating sensor data. This is then fed into ML classifier that discriminates rope pulling from non-rope pulling on a per-window basis. To locate rope pulling segments more accurately, we then apply a procedure that translates window labels into labels of individual samples. In the final step, the sequence of predicted labels, one for each time point, undergo temporal smoothing for removing outliers.

## 4 EXPERIMENT DESCRIPTION

The data for training and evaluating the proposed activity recognition approach was recorded during the lead climbing activities of two climbers (A and B) performed on four lines in two climbing gyms. Five different routes on these lines were climbed in total, with difficulty levels selected according to the skill levels of both climbers. All climbs except one were completed, with climbers reaching the topmost quickdraw before lowering to the ground. Four different datasets (one for each line) were collected; they comprised 17 climbs in total. The average duration of rope pulling activity was 11.5s, and its standard deviation was 2s. The climbs were also video captured in order to later manually label the sensor data. We considered two activity labels, namely, 'not rope pulling' and 'rope pulling'.

Our activity classification approach uses the sliding window technique that has been shown to be effective in previous studies of activity classification [12]. With this technique, the acceleration

[4]https://www.movesense.com
[5]https://apps.apple.com/us/app/movesense-showcase/id1439876677

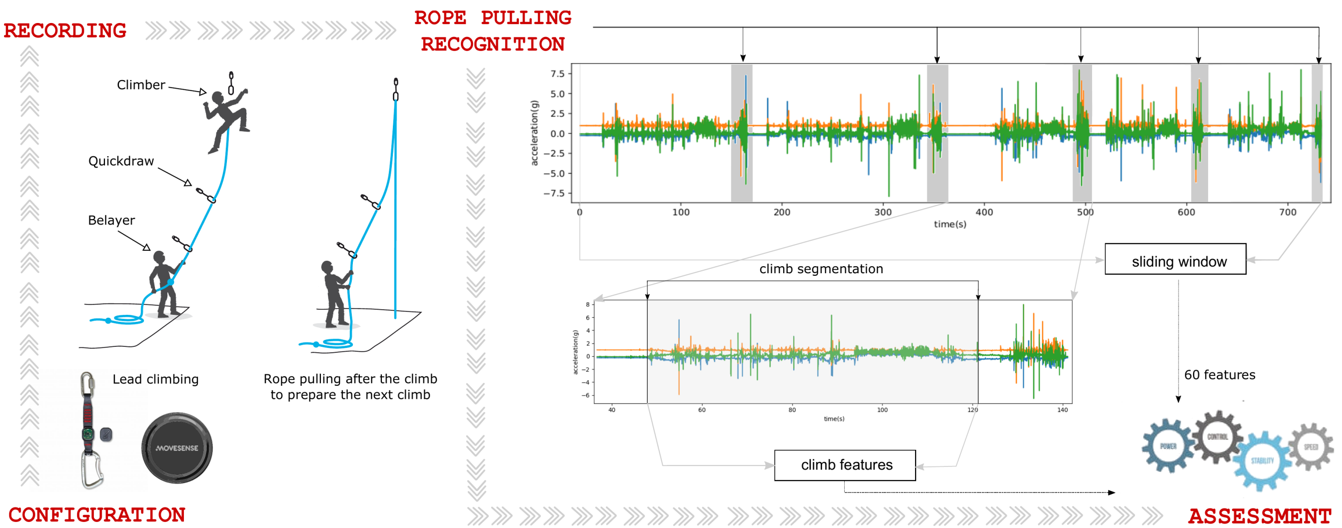


**Figure 1: System overview, see text for description (climbing pictures courtesy by Petzel.com).**

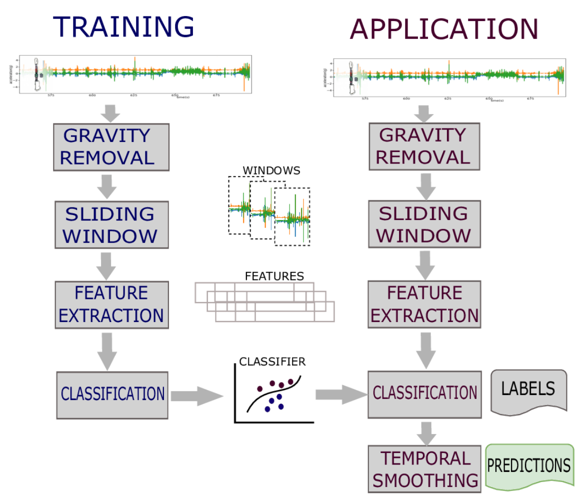


**Figure 2: Overview of rope pulling recognition procedure.**

signal obtained after gravity removal is divided into windows of fixed length. We chose a window size of 400 samples, corresponding to 8 seconds of accelerometer data, because it can sufficiently distinguish rope pulling from the activity of clipping the rope into a quickdraw (i.e., clipping activity). To reduce information loss, we enforced a 95% overlap between two consecutive windows. As a result, 7493 windows labeled as 'not rope pulling' and 236 windows labeled as 'rope pulling' were generated. The ground truth label of each window was assigned to be 'rope pulling' if no less than 90% of its samples belonged to the rope pulling activity.

We calculated time-domain and frequency-domain features that represent the window data in a compact way. We used typical time-domain features such as mean, standard deviation, median, maximum, and minimum of acceleration values. Frequency domain features were generated by applying Fourier transform on a window of sensor data. In summary, we identified 60 features per window. These features were used to train and evaluate supervised classification methods for data windows.

Four classification methods were selected, namely, Random Forest, Logistic regression, CatBoost and AdaBoost [15]. Each classifier predicts a probability that a window spans the rope pulling activity. Predicted window probabilities were then used to estimate a probability that a sample belonged to the 'rope pulling' class in a procedure that simply finds the maximum probability predicted for a window containing the sample. The sample labels are then determined by applying a decision threshold on estimated probabilities.

To evaluate the overall performance of our rope pulling detection system, we performed a 10-fold cross-validation on each dataset individually and globally on the combination of all four datasets. The same training and testing data sets were used for each classifier to avoid any variability arising from different random seeds.

After predictions on a per-sample basis were obtained, simple smoothing for outlier elimination was applied (based on a 400 samples window). The quality of rope pulling segment detection was estimated using the Jaccard index-based measure. The index represents the ratio between the size of intersection of the actual and predicted rope pulling segments and their union size. Shown results represent the average test classification result of each train-test repetition.

## 5 RESULTS AND DISCUSSION

The results of the 10-fold cross-validation performed on the combination of the four datasets clearly show that Random Forest outperforms the other investigated classifiers. Table 1 reports the precision and recall metrics when a standard decision threshold of 0.5 is applied to the raw probability that a sample is predicted to be in the 'rope pulling' class.

Random Forest was further used in 10-fold cross-validation performed on each dataset individually. Each sequence of predicted 'rope pulling' samples was regarded either as true positive (TP) or

**Table 1: Performance of rope pulling detection using different classifiers on raw prediction results.**

| Method | Precision | Recall |
|---|---|---|
| Random forest (n=100) | 0.85 | 0.87 |
| CatBoost | 0.57 | 0.92 |
| AdaBoost | 0.70 | 0.93 |
| Logistic regression | 0.72 | 0.78 |

false positive (FP) depending on whether the sequence overlapped with the 'rope pulling' sequence on the basis of the ground truth labels (GT). Thus, the sum of TP and FP sequences represents the number of rope pulling occurrences as predicted by the classifier.

**Table 2: Performance of rope pulling detection using the random forest classifier on different datasets.**

| Dataset | GT | TP | JI | FP |
|---|---|---|---|---|
| Salewa | 5 | 4 | 0.86 | 0 |
| Vertikale1 | 4 | 4 | 0.92 | 0 |
| Vertikale2 | 4 | 4 | 0.99 | 0 |
| Vertikale3 | 4 | 4 | 0.95 | 0 |
| Overall | 17 | 16 | 0.93 | 0 |

Table 2 shows the computed scores. Additionally, the average Jaccard index of similarity between the predicted intervals of rope pulling and the ground truth is shown in the column JI. Overall, the experiments resulted in the detection of 16 out of 17 rope pulling activities, with the average Jaccard index of 0.93 (1 indicates perfect overlap).

Our results indicate that the recognition system presented here is able to detect with high precision both the number of rope pulling activity occurrences in a session and the activities spanning times. However, there is potentially a trade-off between the two goals which can be controlled by the decision threshold parameter.

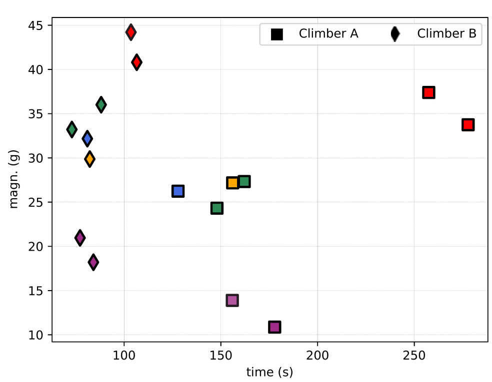


**Figure 3: Comparison between the climb duration and the quickdraw movement magnitude for two climbers on five different routes (climbs on the same route are represented with the same color).**

After having identified the rope pulling segments, we applied a threshold of 0.5g on the (gravity removed) motion magnitude of the enhanced quickdraw to detect the starting time point of each subsequent climb. The sixteen segmented climbs, completed without a fall, on four different lines, and performed by two climbers, were then represented along two dimensions. Climbing time was represented on one axis as an obvious measurement of climber's ability on a given route. It represents the time passed from the moment the climber clipped the rope through the sensor-enhanced quickdraw until the climber pulled the rope. The second axis reflects the cumulative motion magnitude $M$ of the sensor-enhanced quickdraw during a climb per unit of time:

$$M = t^{-1}\sqrt{\sum_{i=0}^{N} a_x(i)^2 + a_y(i)^2 + a_z(i)^2} \qquad (1)$$

In the equation, $a_x$, $a_y$, $a_z$ are acceleration measurements along the $x$, $y$ and $z$ axes at the observation times $i = 1, \ldots, N$, and $t$ is the duration of the climb in seconds.

The magnitude axis captures the overall intensity of sensor-enhanced quickdraw movements during a climb. Clearly, this quickdraw is affected when the climber grabs and pulls the rope up to clip it into the following quickdraw. However, as the rope is attached to the climber's harness, the signal captured from the quickdraw exhibits a higher magnitude when the climber's center of mass moves away from and towards the climbing wall throughout the climb compared to when the climber's center of mass is consistently close to the wall. The results presented in Figure 3 illustrate these opposite movement strategies, i.e., one that is slower but uses less energy for the climb to be successfully completed (climber A) while the second requires more energy, but faster, for successfully completing the climb (climber B).

## 6 CONCLUSIONS AND FUTURE WORK

In this article, we have addressed an activity recognition problem by using a sensor embedded in the climbing-wall (smart quickdraw). The obtained results show that the applied ML methods, in particular a Random Forest classifier, can be effectively used to detect the target rope pulling activity in a continuous stream of accelerometric data. There are some limitations to our work. Firstly, the collected datasets contain only one type of rope pulling (when a person pulls the rope from the first quickdraw); however, climbers sometimes pull the rope from the opposite side i.e., the top located quickdraw. In addition, we did not evaluate the system performance for a large number of different routes and participants performing rope pulling (there were two persons who pulled the rope in the current study). Further tests should reveal whether the recognition system is subject- or line-dependent by employing leave-one-out cross-validation. Of immediate interest is to detect the activity of clipping the rope into a quickdraw. This would be especially useful for extending the proposed systems for recognizing the route of a recorded ascent. We are also working with expert climbing trainers in order to introduce the proposed solutions into their routinary training programs.

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