Automated Recognition and Difficulty Assessment of Boulder Routes

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Abstract. Due to fast distribution of powerful, portable processing devices and wearables, the development of learning-based IoT-applications for athletic or medical usage is accelerated. But besides the offering of quantitative features, such as counting repetitions or distances, there are only a few systems which provide qualitative services, e.g., detecting malpositions to avoid injuries or to optimize training success.

Therefore we present a novel, holistic, and sensor-based approach for qualitative analysis of asynchronous, non-recurrent human motion. Furthermore, we deploy it to automatically assess the difficulty level of boulder routes on basis of climbing movements. Within a comprehensive study encompassing 153 ascents of 18 climbers, we extract and examine features such as strength, endurance, and control and achieve a successful classification rate of difficulty levels of more than 98%.

Keywords: Machine learning · Activity recognition and assessment Climbing and bouldering

1 Introduction

Applications targeting usage within the athletic context and based on smartphones as well as on wearables are ubiquitous by now. Commonly, they provide customized workout plans or count quantitative qualities, while the provision of qualitative feedback exists only sparsely. Therefore, we developed a procedure for qualitative analysis of climbing motion in order to automatically assess the difficulty of boulder routes. In that context, the term boulder route comprises relatively short climbing routes of significantly higher difficulty (compared to normal climbing routes). Due to their commonly low height, they are climbed without safety equipment. Because of the varying and merging complexities of boulder routes as well as the strong dependence on a climber's individual skills, an impartial assessment of a route's level of difficulty is a tough task. In the best case, consequences of an incorrect assessment may be the frustration of a climber or minor injuries due to unfamiliar moves or physical overload. But in the worst case, severe accidents and fatal injuries may occur (e.g., due to a climber's lack of

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skills, wrong appraisal, or hubris) and lead to complex, dangerous, and expensive rescue expeditions.

In order to solve such issues, we developed a distributed sensor system capable of holistic capturing and analysis of recurrent human motion in real-time [1,2]. Now, we extend the underlying concepts and develop a novel procedure for qualitative motion assessment relying on asynchronous, non-recurrent, and multi-dimensional timeseries (see Sect. 3). In order evaluate its capabilities we conducted a study encompassing climbing data of 18 participants for 153 ascents on different boulder routes which are labeled with difficulty levels of the Fontainebleau technical grades scale (see Sect. 4). During analysis we prove that our approach is capable of assessing difficulty levels of boulder routes with a success rate of more than 98%. Finally, Sect. 5 sums up our findings, discusses open issues and provides an outlook onto future research.

2 Related Work

In the following, we present existing work dealing with human activity recognition as well as the analysis of climbing techniques and climbing style. Pansiot et al. show that it is possible to distinguish different climbing styles by extracting features which reflect a climber's fluidity, speed, endurance, and strength-to-weight ratio out of an ear-worn accelerometer [6]. Ladha et al. present ClimbAX, a system which also tries to assess a climber's skills by utilizing similar features extracted from two hand-worn sensors [5]. Both approaches provide interesting input concerning qualitative feature engineering for climbing activities. Kosmalla et al. introduced a concept for automated recognition of climbing routes and presents state-of-art results for that use-case [4]. Still, this approach is not capable of a more generic classification which is necessary to determine a routes level of difficulty in an automated, generic, and precise way. In [2] we present a distributed sensor system called SensX, which allows to capture the whole human body's acceleration and rotation information among other data (i.e., lighting, temperature, barometric pressure, etc.). In [1] we utilize this system as a basis for qualitatively assessing complex and recurrent human motion and demonstrate its capabilities for the use-case of body weight exercises. Thereby, we present state-of-the-art results with a successful classification rate of 99.3% for qualitative assessment and 100% for sheer activity recognition. Though this concept is not suitable for processing asynchronous, non-recurrent motion information, it still functions as a basis for our concept, which is introduced in the following.

3 A Concept for Automated Assessment of Boulder Routes

In contrast to the assessment of recurrent human motion as proposed in [2] climbing activities may not be described by features like similarity, periodicity, or runtime. One reason for the difficulty of using temporal features is that different boulder and climbing routes are of significantly varying lengths and consistencies. Together with skill-dependent ascent times, that makes it hard to find generalizable, time-dependent features for a whole climbing activity. The lack of periodicity results in the fact, that comparison to qualitatively labeled patterns is also not feasible, e.g., a pushup of good quality vs. one of bad quality. To overcome those issues, we use some assumptions based on climbing theory: an increased level of route difficulty is indicated by inaccurate gripping and increased use of strength during transition periods, while a trembling of the climber's limbs occurs more often within rest periods because of exhaustion and imperfect control. The core skills *control*, *stability*, *speed*, and *economical use of strength* are harder to achieve for difficult routes and therefore seem suitable as a theoretical basis for feature engineering [3,5,6].

3.1 Tracking Human Motion Information

In order to track rotation, acceleration, and temporal information occurring while climbing, we applied the SensX sensor architecture mentioned in Sect. 2 as a technical basis. It allows tracking of the human body's limbs and provides an integrated device for realtime processing of incoming sensor data. The four external MBientLab sensor platforms (right arm, left arm, right leg, left leg) provide sample rates of roughly 40 Hz while the processing unit (chest) provides 50 Hz for acceleration and 100 Hz for rotation data. All devices are connected by Bluetooth Low Energy (BLE) and are synchronized by the processing unit. Output of the SensX system are 30 individual sensor data streams: acceleration (X-, Y-, and Z-axis) and rotation (X-, Y-, Z-axis) for 4 external sensor platforms plus the processing unit.

3.2 Preprocessing and Feature Engineering

Subsequently, we describe our advance towards the extraction of an expressive feature set. First, the actual climbing activity is identified and segmented into transition and rest periods (see Sect. 3 and Fig. 1a). Afterwards, we extract our features needed later on for supervised learning.

Segmentation. Generally, a climbing activity takes place in between a temporal interval Δt and has a start time t_s as well as an end time t_e. For further analysis, this interval needs to be distinguished from interfering activities first, e.g., walking or standing. Therefore, an extended approach of [5] respecting the climber's hands positions for activity recognition is utilized: Fig. 1a depicts the acceleration of the right hand including t_{sr} and t_{er}. Within our sensor setup, the hand's acceleration along the Y-axis indicates, whether the climber's arm is currently oriented upwards or downwards.

Using that assumption, we sequentially process the acceleration information of both hands in an overlapping sliding window of 750 ms length. If the mean acceleration in a frame is greater than zero, the arm points upwards and a

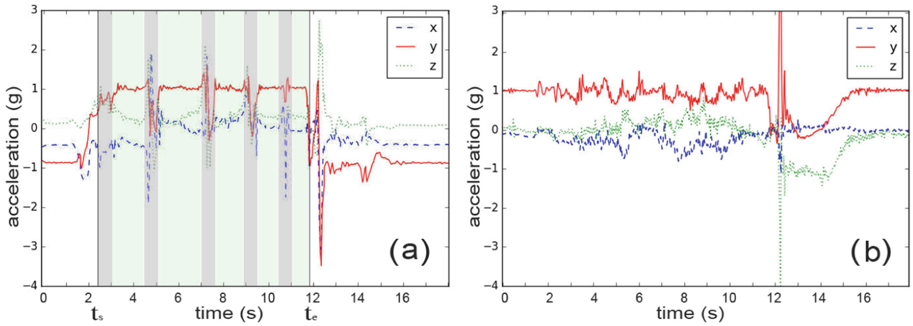

Fig. 1. (a) Acceleration of the right hand during a boulder session with rest (green) and transition periods (grey), (b) shows the chest sensors acceleration. (Color figure online)

describing flag f is set `true`. If both arms point upwards for multiple frames, the climbing activity has started and t_s is marked by the beginning of the first frames where f_r and f_l are `true`. The climbing activity ends as soon as both hands are pointing downwards for multiple frames, whereby t_e is indicated by the beginning of the first frames where f_r and f_l are `false`. In order to prepare for the actual feature extraction, the climbing activity now becomes segmented into rest and transition periods. The sum of the acceleration's standard deviations (X, Y, Z) indicates the released energy potential for each window frame: $S = S_x + S_y + S_z$. If S is greater than an empirically determined threshold, the frame belongs to a transition period, else it indicates a rest period.

Feature Extraction. Based on the core skills mentioned in Sect. 3, we extracted 163 features for each boulder route out of the before segmented rest and transition periods. Each external platform, is described by $2 * 9 * 2 = 36$ features (9 transition period features and 9 rest period features for acceleration and rotation, respectively). Broken down to each period category we use (1) the average means of all axis m_x, m_y, and m_z, (2) their standard deviations s_x, s_y, s_z, (3) the maximum value of the individual sums of all standard deviations of all existing periods within a category s_{smax}, (4) their average mean s_{smean} and (5) the standard deviation of all sums of standard deviations s_{sstd}. E.g., in case of transition periods, consistent values for (1) and (2) imply a stable *control* and *stability*, while (3), (4), and (5) give hints onto the amount of expended energy and therefore strength. In case of rest periods, a higher value implies a lack of control and stability. As depicted in Fig. 1a, the information provided by the processing unit's sensors is much less distinct than that of the external sensor devices (see Fig. 1b). This makes it hard to categorize it into transition and rest periods. Reason for that is the fact that during climbing the limbs are much more in motion than the chest. Therefore, we extracted only 18 features for both period categories together. Finally, we added the ascents duration Δt as a single temporal feature to the created feature vector.

4 Evaluation

For performance evaluation, we conducted a study encompassing 18 climbers performing 153 ascents for 13 different boulder routes. 11 participants were beginners while 7 had climbed or bouldered before – in average the participants had 1.69 years of relevant experience. The 13 routes were categorized into the three color groups *blue*, *sweden* (yellow and blue), and *green*. Each color matches a difficulty range of Fontainebleau technical grades, the most widely used grading system for boulder routes in Europe. According to that, blue is mapped to the grades 1a-2c, sweden encompasses 3a-4b and green matches 4b-5c. In order to enable as much participants as possible to complete the whole study, the tracked routes were of comparably low difficulty.

4.1 Automated Identification of Difficulty Levels

During evaluation, we utilized different supervised machine learning algorithms which are common in related work as well as AutoWeka for automated hyper parameter optimization (HPO). Preceding experiences during the analysis of recurrent timeseries made us assume initially that a sensor setup which covers all limbs as well as an athlete's chest is perfect analyzing athletic movements. But as depicted in Fig. 1c, the chest sensor provides only vague information for climbing activities (e.g., compared to the hand sensor, see Fig. 1a). Hence, we developed a more fine-grained evaluation approach and examined different sensor configurations as well as their influence onto the classification results, as shown in Table 1. As indicated before, the inclusion of the chest sensor's features never improves the results significantly (see Random Forest (RF), Support Vector Machine (SVM)) while in other cases the results are even better if the chest features are not observed at all (see C4.5, Naive Bayes (NB), HPO). In general, the chest sensor's features achieve comparably low success rates if examined isolated. The best results are achieved by using only the limb's features and

Table 1. Classification results for different classifiers and sensor configurations (all sensors, hands only, legs only, chest only, limbs only) and the average training time.

Classifier	All	Top	Bottom	Chest	Limbs	Duration (avg.)
Random Forest	79.74%	74.51%	71.24%	64.71%	79.01%	104 ms
C4.5	67.32%	57.52%	58.82%	56.73%	68.63%	20 ms
Support Vector	86.93%	74.51%	85.0%	75.82%	86.27%	40 ms
Naive Bayes	71.24%	66.67%	62.09%	49.02%	75.82%	8 ms
HPO	89.54%	79.74%	82.34%	60.78%	98.04%	327 ms

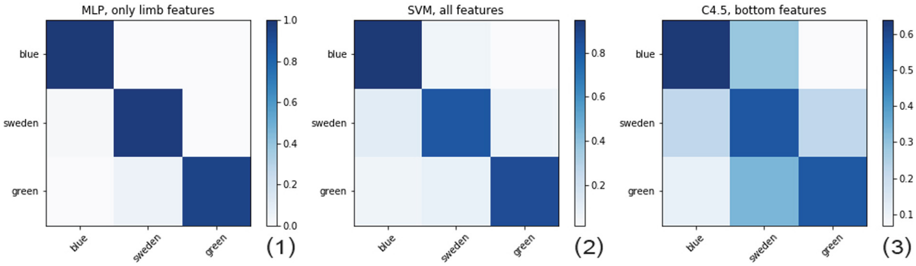

Fig. 2. Confusion matrices for classification results: (1) MLP and only limb features; (2) SVM and all features; (3) C4.5 and only bottom features. (Color figure online)

building our model with an hyper parameter optimized Multilayer Perceptron (MLP), a neural network which has a nonlinear activation function and utilizes backpropagation for training purposes. Hence, we are able to classify the difficulty level of different routes with a success rate of 98.04%. Figure 2 shows the distribution of classified instances for different setups and classifiers within confusion matrices. Especially in (3) it is strongly apparent, that wrongly classified instances are mostly assigned to a neighboring level of difficulty. This illustrates that a color always contains a range of difficulty grades and that neighboring colors may also encompass intersecting grades.

5 Conclusion

Within this paper, we presented a novel approach for analyzing asynchronous and non-recurrent human motion. Therefore, we first track climbing motion with the SensX sensor system, then we detect and segment climbing activities from interfering activities and develop an expressive feature set which is capable of describing non-recurrent and asynchronous human motion, i.e., climbing, in a qualitative way. To validate our approach and to demonstrate its capabilities, we conduct a comprehensive study and classify different difficulty levels of boulder routes with a success rate of more than 98%.

But despite these promising results, we are also aware of still unsolved challenges. E.g., a more fine grained classification concept could solve issues with incorrect assignments of instances to neighboring difficulty levels. Moreover, we currently regard only routes of easy and intermediate difficulty while characteristics of tough routes such as strongly overhanging rocks and tiny grips are not depicted within our feature set. These issues as well as others are subject of ongoing research.

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