ClimbAX: Skill Assessment for Climbing Enthusiasts

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ABSTRACT
In recent years the sport of climbing has seen consistent increase in popularity. Climbing requires a complex skill set for successful and safe exercising. While elite climbers receive intensive expert coaching to refine this skill set, this progression approach is not viable for the amateur population. We have developed *ClimbAX* – a climbing performance analysis system that aims for replicating expert assessments and thus represents a first step towards an automatic coaching system for climbing enthusiasts. Through an accelerometer based wearable sensing platform, climber's movements are captured. An automatic analysis procedure detects climbing sessions and moves, which form the basis for subsequent performance assessment. The assessment parameters are derived from sports science literature and include: power, control, stability, speed. *ClimbAX* was evaluated in a large case study with 53 climbers under competition settings. We report a strong correlation between predicted scores and official competition results, which demonstrate the effectiveness of our automatic skill assessment system.

Author Keywords
Sports analysis, Climbing, Skill Assessment, Activity Recognition

ACM Classification Keywords
H.1.2 User/Machine Systems I.5 Pattern Recognition: J.4 Social and Behavioral Sciences

INTRODUCTION
The sport of climbing has become increasingly popular and is now widely enjoyed as a recreation activity as well as a competitive sport. For example, in the UK the sport "has been on a upward trend since 2005" with a continuous increase in participation [10]. The Italian Alpine Club, which is the world's largest, reports the sport in general has had a population growth of 10% since 2009 [9]. As a recreational activity climbing holistically improves both physical and mental fitness, provides a basis for social interactions, and is a way to enjoy the outdoors. Climbing is also being recognised as a competitive activity, and was considered for inclusion in the 2020 Olympics [22].

Similar to other sports, professional climbing requires physical conditioning, applied sports science and training. Elite climbers follow strict training programmes defined with the assistance of and monitored by a coach. In a typical session, a coach will assess the climber through observation and then provide feedback by commenting on their technique, or suggest training routes that will assist in addressing weaknesses. At amateur level, coaching is also desirable and is a service offered by indoor climbing centres. However, the sheer number of climbing enthusiasts render detailed and frequent feedback from a coach, as it is received by elite athletes, impractical for the amateur. Consequently, amateur coaching is often a group exercise with a typical 1:8 coach to student ratio. The heterogeneity of such groups in terms of climbing skills and experience results in only general feedback rather than in-depth, personalised recommendations and advice.

A wealth of related work exists on self assessment of physical activities using mobile sensing platforms (e.g., [25] and references therein). Commercially available devices, such as Nike fuel band [27] and Fitbit [15], are effective for improving levels of activity simply through providing and visualising statistics to the user that are related to the frequency and —to some extent— fatigue [5]. Some sports self assessment tools are available that focus on the technical skills of the athlete by providing detailed information, not just about the frequency, but also about the quality of the particular activities. Examples include the automatic analysis of golf swings [19] or automatic assistance for swimmers [4].

In line with the aforementioned analysis tools, we have identified the assessment of climbing skill as a case for ubiquitous computing. We have embarked on developing *ClimbAX* – a sensing and analysis system that replicates professional climbing assessment as it is conducted by human coaches.

ClimbAX utilises wrist-worn accelerometers to capture a climber's movements in naturalistic settings. Climbing episodes and individual hold transitions are detected automatically, forming the basis for performance analysis. A variety of performance attributes are developed in this work, which, while being meaningful to climbers, resemble traditional, subjective assessment performed by a professional coach. This climbing skill assessment aims to support future automatic coaching systems that incorporate this objec-

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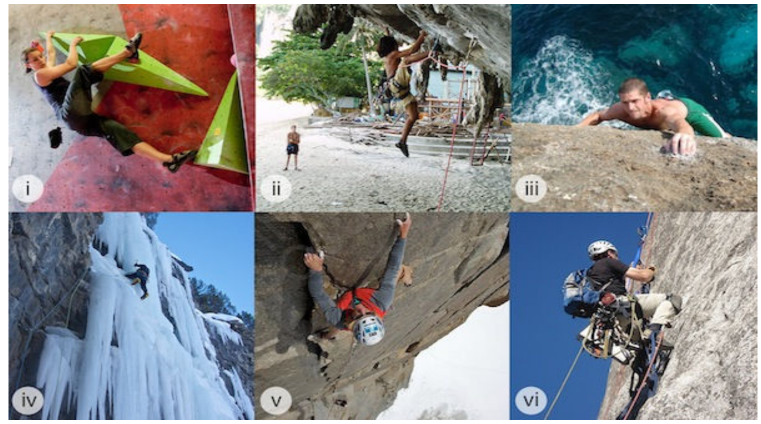
(a) Illustration of the *ClimbAX* assessment system including visualisation of analysis results produced.



(b) Examples of climbing sub-disciplines: Indoor bouldering; Sport climbing; Deep water solo; Ice climbing; Traditional climbing; Aid climbing (*i* to *vi*)

Figure 1. Overview of the *ClimbAX* system for automatic climbing skill assessment and its potential application cases. See text for description.

tive performance information to devise training plans tailored to the individual.

ClimbAX records the climber's movements using a wrist-worn sensing platform that logs high-resolution, tri-axial accelerometer data. This platform is small and sturdy, and does not hinder the climber in their activities. The aggregated data is then processed using an unsupervised analysis procedure, which automatically:

i) filters out climbing from background activities;
ii) segments climbing sessions with respect to transitions between *holds*, i.e., those moments where the climber remains stationary (fixating themselves on the face they are scaling); and
iii) performs climbing skill assessment based on an objective quality scoring scheme.

We evaluated our assessment system in a large field study in a premiere indoor climbing centre assessing the performance of 47 participants of an open bouldering competition event and 6 climbers practicing sport climbing.

The sensing and analysis system presented in this paper allows amateur climbers to track a set of physical performance skills, which can be used either for self-directed training or as a basis for external coaching, and thus improve their performance whilst maintaining health and safety. Figure 1 illustrates the developed system and its potential application cases. Objectively measuring climbing relevant parameters represents an important building block for an automatic coaching system as we are aiming for with *ClimbAX*.

CLIMBING AS A SPORT

The term *Climbing* is used to collectively group many sub-disciplines each having their own distinctions relating to terrain type, accepted ethics regarding protection and tactics used to ascend [18]. Figures 1(b) shows examples of the most widely performed sub-disciplines of climbing.

Popular types of climbing are: *i) Bouldering*, which involves the ascent of relatively low level routes on free standing boulders with just a crash pad to protect the climber in the case of a fall; and *ii) Sport climbing*, where the climber clips their rope into bolts that are pre-placed into the rock, and in case of a fall, a second person ("belayer") will hold fast the rope (with assistance of a friction device) to prevent the climber hitting the ground. Further outdoor climbing sub-disciplines include: *iii) Deep Water Solo* (also known as *Psicobloc*), where the climber uses water below to break a fall; *iv) Ice climbing*, where the climber uses the assistance of crampons and ice tools to ascend; *v) Traditional*, a discipline that employs a strict ethic that all protection placed in the rock must be placed by hand and be removable without damaging the rock; *vi) Aid climbing*, where the climber is permitted to use placed protection as hand and foot holds. *Alpinism* is another discipline that combines aid- and ice climbing at high altitudes. Bouldering and Sport climbing are also frequenty practiced indoors on man-made walls, often constructed from plywood, using shaped resin holds.

Dangers and Difficulties

Climbing carries risks both in the form of objective danger (for example, a rock falling) as well as an injury through poor judgement of the condition of the terrain, or through poor climbing performance. Little can be done regarding the former other than carefully assessing the general conditions (e.g., weather, composition of the targeted face to be scaled), whereas the main influencing factor for the latter is lack of experience and misperception of one's own skills [36]. Unrealistic judgments can lead to wrong decisions regarding the individual appropriateness of particular climbing routes, which can have fatal consequences.

The decision whether or not to embark on a particular route is heavily influenced by knowledge of the climber's abilities, which is typically gained through comparison to others who have already completed the particular route. Making objective comparisons between climbers' abilities can lead to both more informed and confident decisions regarding whether a particular route is appropriate for an individual.

Climbing routes are typically ranked according to their difficulty using established grading schemes, such as the internationally recognised French grading system for sport climbs or the Hueco "V" grading system for boulder problems [18].

Gradings typically do not transfer well between sub-disciplines. However, they share the underlying principle of judging how difficult climbs are technically. In the case where there is an apparent objective danger (often judged by the outcome of a fall) a second grade is often given that can be used to interpret the "seriousness" of the route. In the British Traditional System, this grading is descriptive rather than numeric. For example, a route may be classified as "Difficult" or "Very Severe" [18].

What it takes to get high

Across its sub-disciplines climbing requires a range of physical abilities. For example, climbing large mountain routes requires very good all round stamina, endurance and tolerance to high altitudes, whereas challenges linked to bouldering are often gymnastic in nature and require physical strength, good general coordination, and muscular flexibility. Furthermore, within each sub-discipline there is also scope to specialise for a particular type of terrain. Some climbers for example prefer scaling steep overhanging rocks, which requires very good upper body strength. Others focus on routes that consist of large numbers of hard individual moves, which necessitates power endurance. Despite this diversity all climbers need to possess a core skill set, which subsumes at least four main physically trainable competencies: *i)* Power used to transition between holds [31]; *ii)* Control over limb movement [34]; *iii)* Speed of ascent; and *iv)* Stability whilst on a hold [21, 38].

Investigating the reasons for good or bad climbing performance, some studies have gone as far as measuring plasma cortisol (stress hormone) in climbers during and after high stress activities [13]. Positive correlations to confidence as well as to somatic and cognitive anxiety in climbing were found. Other studies have measured heart rates as both fatigue and stress indicators. These however, did not unveil any insight due to muscles operating in anaerobic state during climbing [24]. In contrast to such biochemical parameters the climber's experience is difficult to assess. Experience helps a climber to identify the most efficient way to climb through a challenging sequence of moves, and it can help identify the most likely weather conditions that will result in a successful ascent (climbing is highly dependant on rock friction which increases as temperature decreases). In either case it is difficult to reason about the mental state or experience of a climber other than through observing how they perform physically.

It has been demonstrated that parameters relating to the physical performance of a climber can be measured at the interface of the hand and the hold. These parameters vary from core body strength to balance and contact strength [17]. Related studies have exclusively used holds instrumented with strain gauges or vision based systems where climbers were instrumented with markers. While these methodologies demonstrate the validity of the parameters, they are not suitable for deployments in realistic settings. Only very few and rather explorative attempts to automatically asses climbing skills in a real-world context have been undertaken thus far. For example, Pansiot *et al.* attached an accelerometer to a climber's head for recording their movements [28]. In a small study with 4 participants they derived climbing skill parameters, which although interesting, did not map to any recognised parameters from the sports science literature.

AUTOMATIC CLIMBING PERFORMANCE ASSESSMENT

The key to performance improvement in climbing is both increased frequency of exercise [11] and training specific weaknesses and elements of technique [21]. In the elite class these training goals are typically managed with the assistance of a coach. Although a direct transfer of such manual coaching programs to the population of amateur climbers is desirable, resource limitations render expert coaching impracticable. Alternatively, automatic assessments have the potential to make coaching more widely accessible.

Structured and guided self-monitoring and self-assessment represent a reasonable alternative to costly professional coaching. A few technical systems have been developed that support amateur climbers in keeping track of their exercises. For example, smart phone applications are available that walk climbers through sets of fixed routines and record the date they were completed; essentially corresponding to an electronic climbing diary for retrospective (manual) analysis [6, 8]. Such technology supported climbing diaries (and variants thereof) can effectively support climbers in keeping up regular exercising or even increasing participation frequency, which in general has positive effects on their health [14].

Automatic coaching aids for climbing are required to not only report the frequency and duration of exercise but also a performance breakdown that is presented using terminology that is familiar to the sport. *ClimbAX* has been designed to comply with these requirements. Figure 2 gives an overview of our system. Movements are captured using small, wrist-worn sensing devices, which are *configured* to *record* tri-axial acceleration data with high temporal resolution. After a session (which can contain multiple climbs) the sensor data is uploaded to an analysis platform where climbing orientated data is automatically filtered out (*climb segmentation*) and the moves within each climb are automatically detected (*move segmentation*). Based on the extracted moves, the actual *assessment* is then performed, which is informed by standard climbing grading schemes. Finally, the results are *visualised* both on a session summary basis and at the more fine-grained level of detail corresponding to particular skill criteria from the assessment.

Recording

With a view on practical deployments in realistic, i.e., non-laboratory, climbing scenarios we adopted a body-worn sensing approach for capturing climbing activities. Apart from the advantage of universal applicability due to minimal requirements on existing infrastructure (such as independence on calibrated camera setups [33]), a wearable, and thus mobile, sensing platform has the benefit of providing detailed and high-resolution data through direct measurements of the climber's movements. Accelerometry in general has proven very effective for assessments of human movements in a variety of application domains [7]. In line with previous, explorative studies [28, 32] we employ tri-axial accelerometers for our automatic climbing assessment framework.

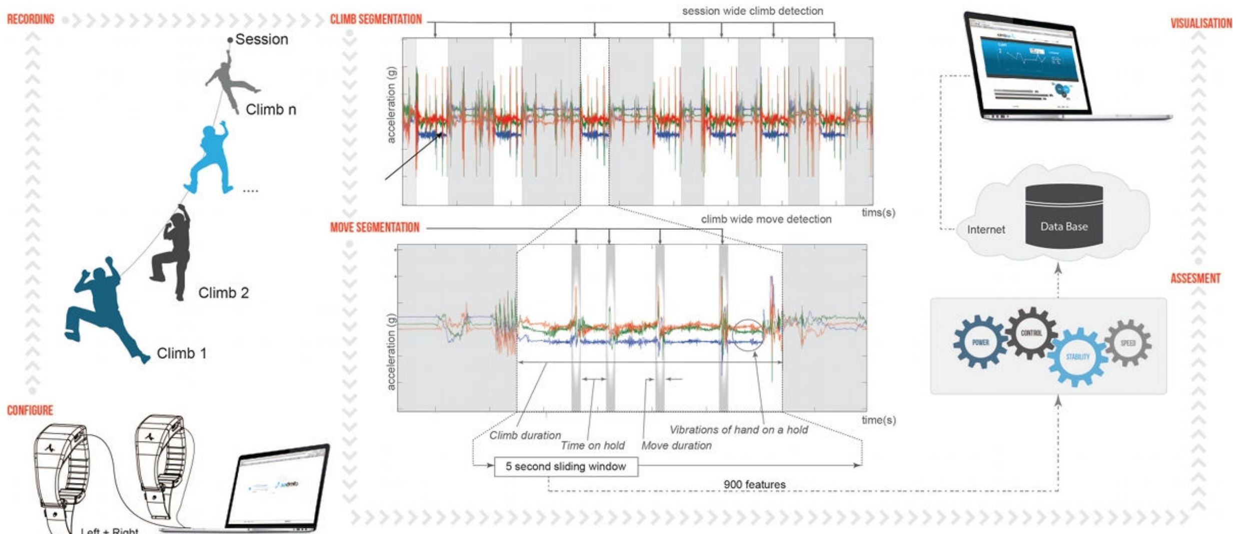


Figure 2. ***ClimbAX*****: System overview (see text for description).**

Transmissions of rotational and vibrational forces in the range of $0.2 - 20$Hz (human movement range) that are exerted through the fingers have been shown to be measurable using an accelerometer placed on the wrist [26]. Consequently, and coupled with the high level of user compliance the wrist affords, *ClimbAX* sensor system was designed around a watch embodiment. Since climbing requires good symmetry and balance we instrument both wrists of the climber in order to capture the movements of the hand that is transitioning as well as the hand supporting the body during transitioning.

Actual applicability for realistic climbing scenarios requires the movement capturing subsystem of *ClimbAX* to record for a minimum of one day, to be light-weight, scratch proof and hypo-allergenic, and to be sturdy enough for operating in chalky/dusty environments. Accordingly we designed a watch-like sensing platform as shown in Figure 3. At its core is a 16-bit, 16 MIPS PIC24 processor, and a 14-bit tri-axial accelerometer (MMA8451Q by Freescale). Sensor readings are sampled at a rate of 100Hz, which provides sufficiently detailed movement information. Samples are stored onto a 4Gb sized NAND flash memory chip along with associated timestamps (accurate to 20ppm and generated from the PIC24). Communication with the device, e.g., for configuration and data download, is based on a micro-USB connector. The internals of the sensing platform are potted into a polycarbonate injection moulded case, which is housed by a silicone wrist band. The band was designed to be thin enough to see the screen through yet still provide a scratch-proof and replaceable fixing method. The design of the band, firmware and software tools were released as *Open Hardware* under the Openmovement platform [39].

Climb Segmentation

Our vision of a climbing analysis system comprises an accessory for assessing climbing activities in a naturalistic setting, i.e., not imposing any additional constraints or requirements that would hinder the core exercise. In line with this, *ClimbAX* detects climbing activities, which alleviates its user from the necessity of interacting with the device, e.g., clicking a button before, during or after each climb.

During every-day activities, arm based movements are subject to what is commonly referred to as *symmetry-bias* [35]. Motions by, e.g., one arm automatically initiate a counter movement by the other arm to keep balance. This symmetry is often used to characterise gait, particularly for neurodegenerative conditions [40]. During climbing this symmetry between the upper extremities is broken as it is crucial for one limb to stay attached to the hold, minimising its movement. Along with tremors related to high intensity activities (vibrations of the hands when on holds caused by fatigue or extreme exertion) this gives rise to specific climbing patterns as they are recorded on the wrists. Our automatic climb detection is based on the analysis of these characteristic movement patterns, which we found are more discriminative than simple assessments of simultaneous upwards wrist orientation with respect to gravity.

Detecting episodes of climbing within continuous streams of accelerometry data corresponds to segmentation of time series data, for which two general processing paradigms exist: *i)* explicit identification of start- and end-points of semantically contiguous bouts (segments); and *ii)* implicit segmentation through extraction of analysis frames and subsequent, isolated classification regarding the patterns of interest [23]. Ambiguity in transitions between non-climbing and climbing activities effectively renders explicit segmentation techniques impractical for climb detection. However, the aforementioned break of symmetry-bias during climbing results in substantially different sensor data distributions for climbing and non-climbing episodes. Exploiting this, we employ an implicit segmentation approach for climb detection using a sliding window procedure that extracts analysis frames thereby integrating sensor data from both wrists.

Our sliding window procedure extracts frames of 5s length with an overlap of 1s, which captures climbing activities very effectively. For analysing symmetry-biases (and breaks

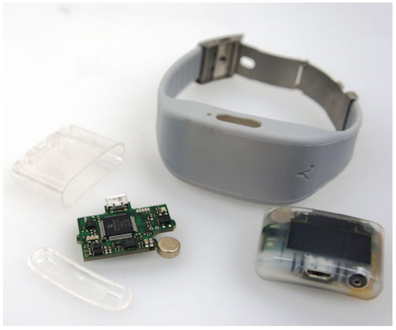


Figure 3. Wearable sensing platform for recording climbing activities that consists of a high-resolution tri-axial accelerometer, OLED screen (not used), on-board processing unit (PIC), battery, and flash memory.

therein) we concatenate the tri-axial sensor readings of both wrists into a unified representation. For these frames we then calculate feature vectors that represent the characteristics of the performed activities in a compact way. We employ a feature learning approach based on Restricted Bolzman Machines (RBM) [20], which has been demonstrated as being very effective for activity recognition tasks [29]. Following the original approach, we employ 900 hidden units to match the input dimensionality (see below). For our climb detection procedure we down-sample the accelerometer data to 30Hz. Cross-validation experiments suggest that this has no adverse effect on the overall effectiveness while at the same time greatly alleviating requirements on the sample sets required for robust RBM training.

Feature vectors are then fed into a statistical classification system that discriminates climbing from non-climbing on a per-frame basis. We have evaluated a number of classification approaches and found that logistic regression works best for climb detection. Finally, the sequences of predicted activity labels undergo temporal smoothing for outlier elimination, resulting in effective segmentation. Figure 4 summarises the climb detection procedure.

Move Segmentation

Even the most complex climbing activities essentially consist of sequences of atomic movement units. These *moves* are defined as:

> *Continuous limb movements that are temporally surrounded by pauses, i.e., static episodes with no significant displacement of the particular limb of interest.*

Consequently, quality analysis of climbing performance is typically based on assessments of individual moves.

ClimbAX follows the general approach of move-based analysis. After climbing sessions have been detected (cf. previous section), we segment moves on a per-limb basis, which is important for the generation of detailed assessment information. Although the aforementioned definition of moves suggests a straightforward implementation through detecting smooth sensor displacement trajectories, there are two things to consider when assessing real-world climbing activities: *i)* Typically moves between holds require hand adjustments to reach a stable and comfortable position. Such adjustments add "jitter" to the beginning and end of the actual reaching

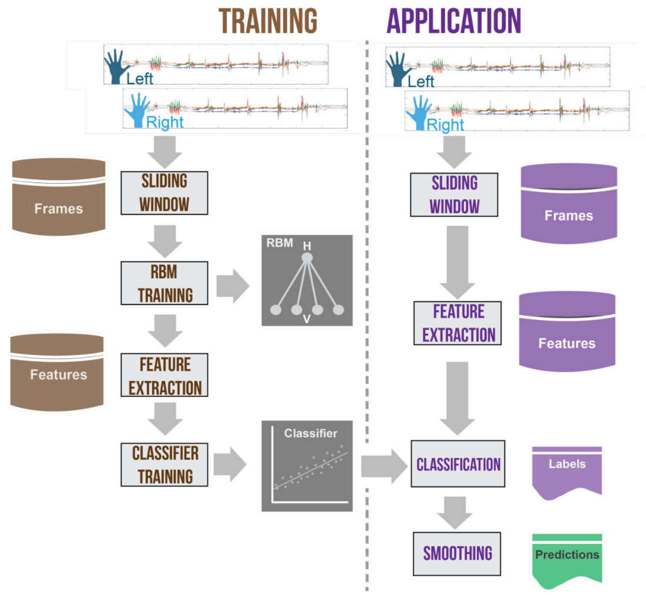


Figure 4. Overview of climb detection procedure: Sliding window frame extraction and feature learning (using Restricted Bolzman Machine – RBM) for capturing characteristics of movement patterns, which are classified using statistical classification backend.

movements; *ii)* Moves can also correspond to the turning of the hand on a single hold without any reaching movement involved, e.g., for repositioning to rest more comfortably or to prepare for the next (reaching) move.

Taking these considerations into account our move detection focuses on segmenting hands being on holds, which is characterised by low energy values of the acceleration signals, interrupted by temporally short high energy episodes. The latter involves a hand moving to a hold, it's adjustment and other climbing activities such as clipping the rope (e.g., for sport climbing; see ii in Figure1(b)). We calculate short-term energies on raw acceleration data using the same sliding window procedure that has been applied for climb detection (previous section). Algorithm 1 summarises the move detection procedure.

Assessment

Quality assessment of climbing as it is performed by professional coaches is —across its sub-disciplines (Figure 1(b))— based on a move-specific analysis of certain key criteria that characterise a set of commonly accepted core skills every climber needs to possess and develop [28]:

Power – the ability to transfer isometric strength into a move. Holds that are further apart will require a climber to be more powerful to transition between them.

Control – the ability to transition smoothly between holds. Often a climber is required to shift their centre of mass to enable a hold transition to be made, which requires both core body strength and balance. Poor control will result in jerky limb movements whereas good control corresponds to smooth transitions between stances.

Algorithm 1 Automatic Move Detection in *ClimbAX*

Input: limb index l (left or right); energy threshold t; climb segment $\mathbf{s}$, frame length F

Output: moves $\mathcal{M} = \{\mathbf{m}_i(\mathbf{s})\}$ for given climb segment $\mathbf{s}$

procedure DetectMoves($\mathbf{s}$, l, t)

  $\mathcal{M} = \emptyset$ ▷ Initialise moves set

  for all Frames $\{\mathbf{f}\}$ **do** ▷ Sliding window procedure

    Calculate short term energy:

$$E_{\mathbf{f}} = \left(\sum_{i=1}^{F} \mathbf{f}_x(i)^2 + \mathbf{f}_y(i)^2 + \mathbf{f}_z(i)^2\right)^{-1/2}$$

    if $E_{\mathbf{f}} > t$ **then** ▷ Energy thresholding

      $\mathcal{M} = \mathcal{M} \bigcup \mathbf{f}$

    else

      continue

    end if

  end for

  Perform median smoothing ▷ Outlier elimination

end procedure

Stability – the ability to remain composed while holding onto holds. Small or sloping holds are difficult to grip typically resulting in poor stability as postural or finger repositions are required to maintain a stance on a hold.

Speed – defined as timing observation. In most cases, completing a climb in the shortest possible time is desirable.

We aim for replicating expert assessments by measuring the aforementioned core skills in the climbing episodes extracted from the sensor signals.

Intuitively, the power of a climber corresponds to the peak (physical) work they can perform over time, which has been used to assess a climber's arm power in a well controlled experiment in [12]. This immediate measure of the arm's displacement over time, however, fails to capture the context of the move performed, i.e. the perceived quality of the holds and footrests involved in a climbing sequence. This context is nevertheless crucial to gain insights about a climber's abilities. Even a climber with very little power will be able to perform a long reaching and quick move from good quality holds, while the same climber will struggle with small holds that are difficult to grab.

A low quality hold induces high intensity tremors as much strength is required to pull or hang from it. The signal captured from this hand will therefore exhibit a higher signal energy compared to a good quality hold. In order to assess power P for a climb that involves i moves, we measure the relationship between the signal energy E_m^i of the moving hand to the signal energy E_h^i of the hand residing on a hold during a move:

$$p_i = \frac{E_m^i}{E_h^i} \tag{1}$$

$$P = \max\left(\{p_i\}\right) \tag{2}$$

Coaching guides describe *Control* as the smoothness of hand movements during hold transitions [18, 21]. Intuitively a climber that shows good control has a great level of coordination, good timing and moves efficiently between holds. A controlled hold transition corresponds to a smooth movement of the hand, without hesitation, that precisely reaches the optimal hand position on the target hold. Poor control often results in *over-shooting* beyond the hold, hitting the wall during the transition, and high impact forces on the target hold due to imprecision (see Figure 5).

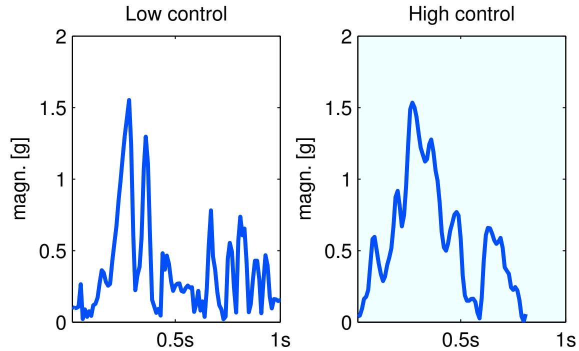


Figure 5. Two example moves demonstrating low and high control. The left plot shows the motion magnitude (gravity removed) from a climber with a low score for control. The right plot shows the same move by the climbing with the highest estimated control.

Control C can thus be characterised as the ratio of energy in short bursts (impacts) against energy in the long run (smooth motion) captured from the moving arm.

$$c_i = \max\left(\left\{\frac{e_t^s}{e_t^l}\right\}_{t \in T_i}\right) \tag{3}$$

$$C = \text{mean}\left(c_i\right), \tag{4}$$

where c_i is the control of move i (over time T_i), while e_t^s, and e_t^l are short-term signal energies calculated using a sliding window with length t_s and t_l respectively ($t_l \gg t_s$).

Stability in climbing is a measure for how well attached the hands remain to the hold while not engaged in a hold transition. Poor stability, i.e., unnecessary movements of the hand while on a hold, is most commonly caused by a combination of poor flexibility and core body strength. These unnecessary movements usually correspond to sharp changes in acceleration when, e.g., the hand position on the hold is adjusted. Stability S for a climb is therefore inversely proportional to the variance of the first derivative of motion magnitude (*jerk*) while the hand is not moving:

$$S = \text{std}\left(\frac{\partial m_h}{\partial t}\right)^{-1}, \tag{5}$$

where m_h is the motion magnitude of each hand on hold.

Coaches use the *Speed* of a climber to asses both their route reading ability as well as their fatigue. While there are many ways to define speed (e.g., time taken to ascend a route, or time between limb movements) we chose to measure speed V as the number of moves per second. This methods is thus insensitive to route length and can be directly derived from the climb and move segmentation outputs.

ClimbAX calculates estimates of these core skills for every detected move and combines the values into a 4-dimensional skill representation $\mathbf{s} = \{P, C, S, V\} \in \mathbb{R}^4$. In doing so we effectively translate continuous accelerometry data collected by the sensing platform worn on both hands of the climber into sequences of core skill values, which is the basis for both individual and comparative assessment, as well as for progress tracking – all at a great level of detail, which replicates and translates to best practice in existing manual assessment.

EXPERIMENTAL EVALUATION

Datasets

Two different datasets were collected in order to evaluate: *i)* the climb segmentation; *ii)* the move segmentation; and *iii)* the automated skill assessment.

The first dataset (*sport climbing*) consists of a total of 42 climbs recorded from 6 participants at two different indoor climbing walls (i, and iii in Figure 7). Participants were asked to wear a set of sensors for the duration of their visit to the climbing wall and to go about their regular climbing activities without any specified protocol. After their climbing session participants were asked to produce a diary containing the exact start and end times of each climb. A climb here is defined as the moment the subject starts climbing until they are back on the ground, i.e., it may contain resting and falls. Crucially the data recorded is not limited to climbing activities but contains other activities such as belaying, walking around, resting, etc.

The second dataset (*competition*) was collected during a local bouldering competition, where a total of 47 subjects performed a single climbing problem, which was part of the official competition set (purple holds in Figure 6). The route was set up with the particular needs of a performance evaluation in mind. Care was taken so that it contains moves that require both control and power, without favouring one particular skill set or side of the body. Participants were recruited among all competitors with no particular preference, resulting in a representative sample of the audience for such competitions. Based on video recordings the recorded data was annotated for climbs and the exact sequence of moves performed by each participant. In addition to the recordings, the competition results for the majority of the participants were also collected. Both datasets are summarised in Table 1.

Dataset	Participants	Climbs	Moves	Scores
Sport climbing	6	42	–	–
Competition	47	47	770	40
Total	53	89	770	40

Table 1. Summary of (annotated) data collected in 2 different studies.

Segmentation of climbing episodes

In order to evaluate the performance of the climb detection described in this work a 10-fold cross validation was performed on the combination of both the *sport climbing* and the *competition* dataset. For each dataset, frames of 5-second length are extracted with a shift of 1 second. The identity of each frame is decided based on a majority vote based on the ground truth annotations. This set of frames is then split into 10 partitions, each containing a continuous segment of the data (with respect to time), which is retained throughout all experiments. An RBM with Gaussian visible units and binary hidden units is trained for 250 epochs for each fold. For each frame, the activation probabilities of the hidden units are retained as feature representation.

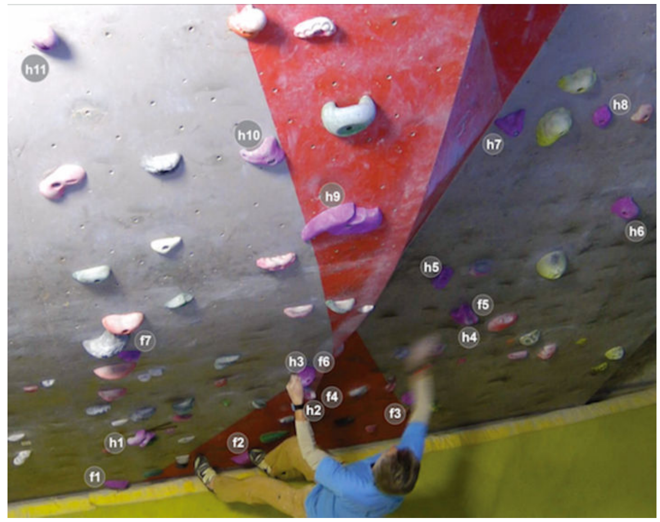


Figure 6. A subject on the route climbed by all participants in the *competition* dataset (purple holds). Increasing numbers indicate the intended sequence of holds (*h* for hands and *f* for feet) although some variation in solutions was observed.

Figure 7. *ClimbAX*: The locations used for data collection: i) Indoor sports climbing wall. ii) Indoor bouldering wall under competition settings. iii) Indoor sports climbing wall with large overhang.

Three different classifiers were trained based on the features extracted by the RBM: *i)* k-nearest neighbour ($k = 1$); *ii)* decision trees (c4.5); and *iii)* standard logistic regression. Results are reported in Table 2. After obtaining the results for each frame independently it is straight-forward to apply temporal smoothing based on a window of n samples and a hamming window. Using a simple threshold to detect a climbing episode heavily improves the recognition results. Figure 8 illustrates ROC curves for the different classifiers after temporal smoothing is applied (based on a 50-sample window). Logistic regression on the raw, 900-dimensional feature representation clearly outperforms all other classifiers investigated.

Method	Precision	Recall	Specificity
c45*	0.43	0.64	0.81
knn*	0.66	0.78	0.91
logR	0.79	0.71	0.96
PCA+logR*	0.80	0.66	0.96

Table 2. Performance of climb detection using different classifiers on raw prediction results (no temporal smoothing).

Dataset	Precision	Recall	Specificity
Sport climbing	0.85	0.88	0.96
Competition	0.88	0.86	0.98
Overall	0.87	0.87	0.97

Table 3. Performance of climb detection using 'logR' after temporal smoothing. The *Sport Climbing* dataset contains approx. 17% climbing activity along with different activities typical for a visit to a climbing centre.

Table 3 illustrates the best segmentation results for the different datasets using logistic regression. Overall the results improve dramatically if temporal smoothing is employed with a precision of 0.87 and a recall of 0.87. The results for the *Sport Climbing* dataset are particularly interesting as they include plenty of activities unrelated to climbing. This dataset was captured during typical visits to a climbing centre and includes activities such was warming up, stretching, drinking coffee, and walking among others. Some activities that are similar to climbing activity are included as well, such as rope handling and belaying. Overall climbing constitutes just 17% of this set, yet it can still be detected very reliably with a specificity of 0.96.

Segmentation of moves

Based on the extracted climbing episodes from the *competition* dataset we apply the process described in this work to extract moves, separately for each limb. Each move is treated as an event, and is deemed detected if it overlaps with an automatically extracted move. Overall this results in a precision of 0.79 and a recall of 0.82. The imprecision of the method is largely due to the boundaries extracted by the climb detection, which may exclude moves at the very start and end of a climb. These boundary conditions have a significant impact on the performance figures since the short climbing sequences in this dataset just contain approx. 10 individual moves per hand (see Figure 6). However, our results indicate that the extracted moves still adequately reflect the climbers' overall skill.

Assessment parameter evaluation

Based on the extracted climbing episodes along with their segmented moves, one set of performance attributes (power, stability, control and speed) is estimated for each climber using the process described above. The competition scores recorded in the *competition* dataset effectively correspond to an objective, unbiased estimate of a participants climbing ability. Out of the 47 participants, 40 handed in a scoring sheet, which provide the basis for the evaluation of a simple linear model. In this experiment, a linear regression is fitted in a leave-one-climber-out cross-validation and used to predict competition scores based on the performance attributes.

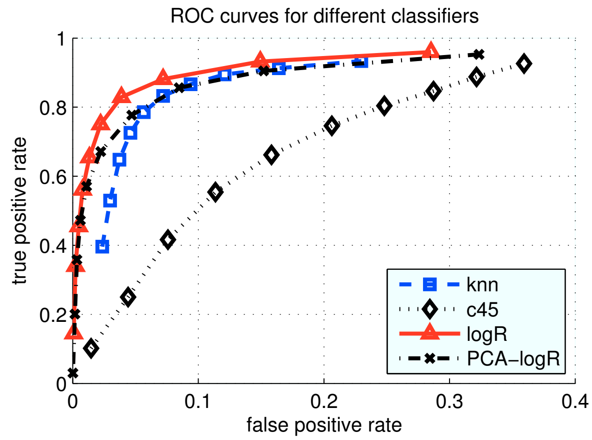


Figure 8. ROC curves of different classifiers for climb detection after temporal smoothing. Logistic Regression on the raw features ('logR') clearly outperforms other classifiers. Its performance remains comparable to KNN if the dimensionality of the features is reduced using PCA to 100 dimensions.

The scatter plot in Figure 9 illustrates the results. The predicted scores show an overall positive correlation to the recorded competition scores of 0.74, indicating that our performance attributes are suitable to capture some elements of climbing skill. This is an extremely encouraging result, as the performance of a climber during a competition is influenced by many things a body-worn sensing system is incapable of measuring (such as mood, form, etc.). Furthermore, since just a single climb is observed from each participant, long term characteristics such as (power) endurance and tiredness can not be observed.

Another parameter that has strong implications on climbing style is that of body-weight. Remaining on the wall, even on very difficult and small holds, requires less strength for a very lean climber. We believe that the route we set for this experiment favoured lean climbers with a transition on a difficult hold (hold *h9* in Figure 6). Inspired by this insight we performed an additional experiment in which climbers with a body-mass index (bmi) of less than 20 are removed from the set. Following the same approach as for the last experiment, the performance improves significantly with an overall correlation of 0.84. A scatter plot illustrating the performance of this reduced set is illustrated in Figure 10.

RELATED WORK

Current best practice for the assessment of climbing activities corresponds to manual observation and judgment, typically performed by an experienced coach. While such expert assessments work well for elite climbers, practical resource limitations prevent generalisation to the large number of amateur climbers. The desire for automated climbing assessment served as the motivation for the development of the *ClimbAX* system presented in this paper.

Monitoring general sports activities using ubiquitous computing technology has become very popular in the recent past. The proliferation of inexpensive, miniaturised sensing hardware together with the availability of sufficient computational power in mobile devices has lead to a wealth of applications

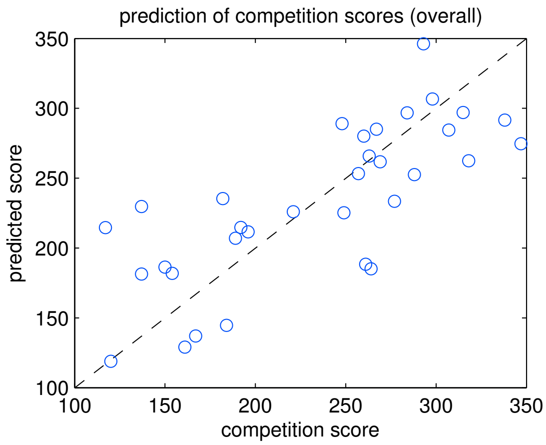


Figure 9. Scatter plot of climbers' performance in the competition, illustrating the correlation between predicted scores and the ground truth (0.76). The estimated performance parameters of each climb $s \in \mathbb{R}^4$ are used to train a linear model in a leave-one-out cross-validation.

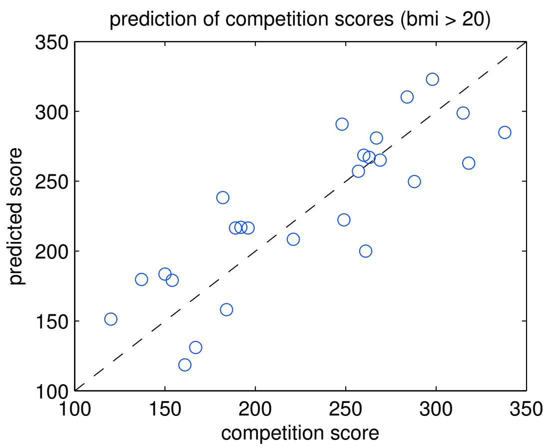


Figure 10. Prediction performance when climbers with a *bmi* of less than 20 are removed from the set. The prediction shows a correlation to ground truth of 0.84.

[2]. Apart from logging sports activities a few systems have also focused on assessments of their qualities. To name but a few examples, Fothergill *et al.* developed an automatic coaching system for rowers [16], Ahmadi and colleagues explored the use of wearable computing for skill assessment in tennis [1], Möller *et al.* described skill assessment in fitness exercises using a mobile phone [25], and Grober instrumented a golf club with accelerometers to analyse the quality of golf swings [19].

Hardly any approaches have so far been published that are related to the automatic analysis of climbing activities. Notable exceptions are the exploration of body-attached sensors as a means for movement analysis in rock climbers [32], and the use of ear-mounted accelerometers for climber performance monitoring [28]. However, both studies have either focused on the exploration of the general feasibility of wearable climbing assessment, or targeted very specific aspects of climbing activities. In contrast, our work goes much further by developing a complete framework for generic skill assessment in climbing activities.

Activity recognition underlying the presented climbing assessment is closely related to gesture recognition using wearable computing techniques, which is one of the major research fields within the ubiquitous and wearable computing community [30]. A large variety of applications has been explored, ranging from analysing activities of daily living, health-related aspects, or work-related activities [3, 37]. A wealth of analysis techniques have been employed, whereas the majority of them focus on discriminating the activities of interest rather than assessing their quality.

DISCUSSION

Climbing has become very popular and is now being enjoyed by a large population who value it as a sociable leisure activity that combines physical activities with outdoor experiences in a unique way. Similar to other sports, climbing requires physical fitness and coordination, and progression can only be achieved through repetitive and dedicated practicing. Elite climbers reach (and maintain) their expertise with the support of individualised coaching. Such coaching specifically targets the improvement of individual weaknesses that are identified by experts who continuously analyse their performance. Unfortunately, such expert coaching and performance assessment is not available for most climbers at the amateur level. As a consequence and especially in the light of the complexity of climbing, many amateurs lose motivation by not making enough progress in developing their skills or even put their health on jeopardy through inappropriate or dangerous climbing.

We have embarked on developing an automatic assessment system that analyses the quality of climbing – *ClimbAX*. Ultimately such a system represents an important building block for a digital, personal climbing coach that replicates individualised expert assessment of climbing skills as it is currently conducted by human coaches. In this paper we presented a body-worn sensing system and explored analysis techniques that effectively segment and quantify measures relating to climbing ability. With the assistance of coaches and sport science literature, four core parameters were designed that are relevant for climbing skills: power, control, stability and speed.

We have demonstrated that an automatic analysis approach based on the combined evaluation of aforementioned core climbing skills correlates to scores achieved under competition conditions. This comparison is, however, limited when used for either very good climbers or absolute beginners. In the case of beginners, not enough data was captured as often the climber fell from the route in the first few moves. In the case of very the elite climbers, the route was not significantly hard enough to test their ability. Our results indicate that climbers with lean body-shape were favoured by the route set for our experiments with much improved results upon their removal from the assessment.

While our results are encouraging, they are just based on a single climb per participant. Crucial aspects such as endurance (defined as resilience to fatigue) are inaccessible to the system and a considerable amount of work necessary until am automatic, personal climbing coach becomes reality.

FUTURE WORK

This work explores the automatic assessment of climbing ability, with the aim to provide a basis for a (semi-) automated, personalised coaching system. However, the transition from raw performance attributes towards individualised training recommendations is not explored. Of particular interest here is to investigate if automated training recommendations are beneficial for a climber's progression and how this benefit compares to that of a dedicated professional coach, which will be explored in future studies.

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REFERENCES

1. A. Ahmadi, D. Rowlands, and D. A. James. Towards a wearable device for skill assessment and skill acquisition of a tennis player during the first serve. *Sports Technology*, 2(3-4):129–136, Feb. 2010.
2. D. Andre and D. L. Wolf. Recent advances in free-living physical activity monitoring: a review. *Journal of Diabetes Science and Technology*, 1(5):760–7, Sept. 2007.
3. L. Atallah and G.-Z. Yang. The use of pervasive sensing for behaviour profiling a survey. *Pervasive and Mobile Computing*, 5:447–464, 2009.
4. M. Bächlin, K. Förster, and G. Tröster. Swimmaster: A wearable assistant for swimmer. In *Proc. Int. Conf. Ubiquitous Comp. (UbiComp)*, 2009.
5. D. T. Barry, T. Hill, and D. Im. Muscle fatigue measured with evoked muscle vibrations. *Muscle & Nerve*, 15(3):303–309, 1992.
6. Beastmaker. `bit.ly/YvAzlR`. accessed: March 11th, 2013.
7. L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu. Sensor-Based Activity Recognition. *IEEE Trans on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, 99, 2012.
8. Climbcoach. `www.climbcoach.org`. accessed: March 11th, 2013.
9. Club alpino italiano. `www.cai.it`. accessed: March 11th, 2013.
10. W. Coldwell. Indoor climbing: the rise of bouldering-only centres. The Guardian Online Edition, `bit.ly/MWPd1m`, 28th June 2012. accessed: March 11th, 2013.
11. P. Cordier, M. M. France, J. Pailhous, and P. Bolon. Entropy as a global variable of the learning process. *Human Movement Science*, 13(6):745–763, 1994.
12. N. Draper, T. Dickson, G. Blackwell, S. Priestley, S. Fryer, H. Marshall, J. Shearman, M. Hamlin, D. Winter, and G. Ellis. Sport-specific power assessment for rock climbing. *The Journal of Sports Medicine and Physical Fitness*, 51(3):417–425, Sept. 2011.
13. N. Draper, T. Dickson, S. Fryer, G. Blackwell, D. Winter, C. Scarrott, and G. Ellis. Plasma cortisol concentrations and perceived anxiety in response to on-sight rock climbing. *Int. Journal of Sports Medicine*, 33(1):13–7, 2012.
14. P. H. Fentem. Benefits of Exercise in Health and Disease. *British Medical Journal*, 308:1291–1295, 1994.
15. Fitbit. `www.fitbit.com`. accessed: March 11th, 2013.
16. S. Fothergill, R. Harle, and S. Holden. Modeling the model athlete: Automatic coaching of rowing technique. In *Proc. Joint IAPR Int. Workshop on Structural, Syntactic, and Statistical Pattern Recognition (SSPR & SPR)*, 2008.
17. F. K. Fuss and G. Niegl. Instrumented climbing holds and performance analysis in sport climbing. *Sports Technology*, 1(6):301–313, Mar. 2009.
18. A. Fyffe and I. Peter. *The Handbook of Climbing*. Pelham Books, 1997.
19. R. D. Grober. An Accelerometer Based Instrumentation of the Golf Club: Measurement and Signal Analysis. Arxiv preprint arXiv:1001.0956, 2009.
20. G. E. Hinton, S. Osindero, and Y.-W. Teh. A fast learning algorithm for deep belief nets. *Neural computation*, 18(7):1527–1554, 2006.
21. E. J. Horst. *Training for Climbing: The Definitive Guide to Improving Your Performance*. Falcon, 2nd edition, 2008.
22. IOC announces new events for Sochi 2014, shortlisted sports for 2020. Olympic.org, `bit.ly/WPhBGU`, 4th July 2011. accessed: March 11th, 2013.
23. E. Keogh, S. Chu, D. Hart, and M. Pazzani. Segmenting time series: A survey and novel approach. *Data mining in time series databases*, 57:1–22, 2004.
24. C. M. Mermier, R. A. Robergs, S. M. McMinn, and V. H. Heyward. Energy expenditure and physiological responses during indoor rock climbing. *British journal of sports medicine*, 31(3):224–228, 1997.
25. A. Möller, L. Roalter, S. Diewald, M. Kranz, N. Hammerla, P. Olivier, and T. Plötz. GymSkill: A Personal Trainer for Physical Exercises. In *Proc. Int. Conf. Pervasive Computing and Communications (PerCom)*, 2012.
26. A. Murgia, P. J. Kyberd, P. H. Chappell, and C. M. Light. Marker placement to describe the wrist movements during activities of daily living in cyclical tasks. *Clinical Biomechanics*, 19(3):248–254, 2004.
27. Nike fuel. `www.nike.com/us/en_us/c/nikeplus-fuelband`. accessed: March 11th, 2013.
28. J. Pansiot, R. C. King, D. G. McIlwraith, and B. P. L. Lo. ClimBSN: Climber performance monitoring with BSN. In *Proc. 5th Int. Summer School and Symposium on Medical Devices and Biosensors*, 2008.
29. T. Plötz, N. Hammerla, and P. Olivier. Feature Learning for Activity Recognition in Ubiquitous Computing. In *Proc. Int. Joint Conf. on Art. Intelligence (IJCAI)*, 2011.
30. S. J. Preece, J. Y. Goulermas, L. P. J. Kenney, D. Howard, K. Meijer, and R. Crompton. Activity identification using body-mounted sensors – a review of classification techniques. *Physiological Measurement*, 30(4):1 – 33, 2009.
31. F. Quaine, L. Martin, and J. Blanchi. Effect of a leg movement on the organisation of the forces at the holds in a climbing position 3-D kinetic analysis. *Human Movement Science*, 16(2-3):337–346, 1997.
32. T. Schmid, R. Shea, J. Friedman, and M. B. Srivastava. Movement analysis in rock-climbers. In *Proc. Int. Conf. Information Proc. in Sensor Networks (IPSN)*, 2007.
33. F. Sibella, I. Frosio, F. Schena, and N. Borghese. 3d analysis of the body center of mass in rock climbing. *Human Movement Science*, 26(6):841 – 852, 2007.
34. M. Testa, L. Martin, and B. Debû. Effects of the type of holds and movement amplitude on postural control associated with a climbing task. *Gait & posture*, 9(1):57–64, 1999.
35. P. Treffner and M. Turvey. Symmetry, broken symmetry, and handedness in bimanual coordination dynamics. *Experimental Brain Research*, 107(3):463–478, 1996.
36. M. F. Twight and J. Martin. *The Extreme Alpinism: Climbing Light, Fast, and High*. The Mountaineers Books, 1999.
37. J. A. Ward, P. Lukowicz, G. Tröster, and T. E. Starner. Activity recognition of assembly tasks using body-worn microphones and accelerometers. *IEEE Trans. Pattern Analysis and Machine Intelligence (TPAMI)*, 28(10):1553–67, Oct. 2006.
38. D. White and P. Olsen. A time motion analysis of bouldering style competitive rock climbing. *The Journal of Strength & Conditioning*, 24(5):1356–1360, 2010.
39. Openmovement sensing platform. `www.openmovement.co.uk`. accessed: March 11th, 2013.
40. G. Yogev, M. Plotnik, C. Peretz, N. Giladi, and J. M. Hausdorff. Gait asymmetry in patients with parkinson's disease and elderly fallers: when does the bilateral coordination of gait require attention? *Experimental brain research*, 177(3):336–346, 2007.