

Smart Belay Device for Sport Climbing—An Analysis about Falling[†]

Heiko Oppel *  and Michael Munz * 

Research Group Biomechatronics, Ulm University of Applied Sciences, 89081 Ulm, Germany

* Correspondence: heiko.oppel@thu.de (H.O.); michael.munz@thu.de (M.M.)

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Abstract: Although sport climbing is generally considered a comparatively safe sport, the injuries that do occur can be more severe than in other sports. With its increased popularity over the last few decades, sport climbing has started to attract people who are unfamiliar with the sport. Especially as a belayer, you are responsible for the climber's safety. For this reason, addressing the issue of safe belaying is necessary. Using an instrumented belay device, we recorded a climber's fall into the rope with varying configurations. By combining this data with machine learning algorithms, we were able to categorize the recordings and extract information about the severity of the fall for the climber.

Keywords: sensor analysis; sport climbing; machine learning; monitoring system

1. Introduction

Monitoring systems are used to supervise the training progress of athletes. In the domain of sport climbing, several studies have been conducted to analyze climbing-specific activities [1–3]. These types of systems can also be used to reduce the likelihood of future injuries, which should always be the top priority in any sport. Several sports, like tennis [4] and soccer [5], conduct research on monitoring devices to supervise their athletes' training and intervene in case of potential injuries. In this paper, our focus is on estimating the severity of the climber's fall, which then can be used as feedback to train the belayer. In an earlier study, we examined a similar approach by attaching an inertial measurement unit (IMU) directly onto the belayer to estimate the impact force [6]. Several configurations were recorded, using a sandbag serving as a substitute for the climber. The best results were achieved with a median error for the impact force of about 4.96%. In the current study, we relied on an instrumented belay device to

- Estimate the impact force in Newton [N] and
- Categorize the type of belaying into dynamic or non-dynamic.

Such a system could be used to perform a post-analysis on the belayer's belaying techniques and further improve their skills to prevent potential injuries.

2. Methods

The first part of the section describes the measurement system and device we used, along with the setup. The recordings we generated with the system were then processed (Section 2.3) in order to perform the analysis (Section 2.4).

2.1. Measurement System and Setup

The belay device with integrated sensors was first introduced by us in [7]. The device enables recording of kinematic sensor information about the device and the movement of the rope. An IMU as well as three bipolar hall sensors in combination with six magnets on a rotation wheel measuring rope movement were integrated.



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The setup was built around a specifically designed system, which was built by Edelrid GmbH & Co. KG (Achener Weg 66, 88316 Isny im Allgäu, Germany) to simulate a climber's fall with an acceleration of approximately $9.5 \frac{m}{s^2}$. The substitute was a truck-tire weighing around 40 kg, which was about 20 kg less than our belayer. The climber and belayer were connected through a rope that was attached to the belayer via the belay device and to the climber using a knot of eight. The rope ran through two quickdraws, where the highest one served as an anchor. Additional friction was not added to the system.

The impact force served as an indicator for the severity of the fall. It was calculated by multiplying the weight of the climber with the maximum occurring acceleration while falling into the rope. As the aim of the study was to analyze and reduce this parameter; therefore, we designed our study to induce a varying impact force. Therefore, we varied

- The amount of slack in the system between 0 m and 0.5 m and
- The type of belaying (either dynamic or non-dynamic).

Dynamic belaying requires the belayer to jump in the direction of the rope to reduce the impact on the climber while falling. Non-dynamic belaying, on the other hand, refers to the belayer standing passively by in case of falling. The two configurations are visualized in Figure 1. Overall, we conducted 44 falls, of which 20 were dynamic and 24 were non-dynamic belaying.

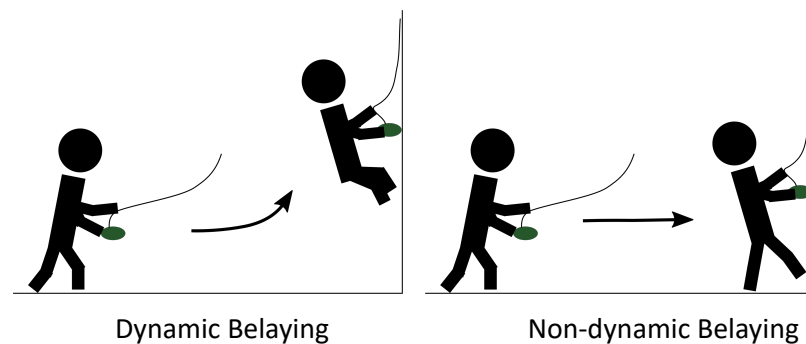


Figure 1. Comparison between the two conducted configurations of dynamic and non-dynamic belaying. In case of a fall, the belayer is always pulled in the direction of the rope (first quickdraw), regardless of the type of belaying. The difference is marked by the movement of the belayer as soon as the fall takes place. From there, the belayer must jump in the direction of the rope. This is referred to as dynamic belaying. Without the additional jump, the belayer would be passively standing by, which is referenced as non-dynamic belaying.

2.2. Segmentation Algorithm

In this paper, we examined how the severity of a climber's fall into the rope can be measured using our instrumented belay device. Therefore, the climber was also equipped with an IMU to record their movement. In the case of a fall, the belay device stopped the movement of the rope due to friction in the system. Therefore, this information is negligible and was further considered in the process of feature engineering. We also eliminated the information about the angular velocity of the device and combined the three axes of the accelerometer by calculating the resultant acceleration, thereby reducing the initial feature space. An example of a fall sequence is visualized in Figure 2. The movement of the rope was registered in this fall, although, with only 3 cm it was marginally low, because of the breaking mechanism that stopped the rope.

Based on the information from the climber, we extracted a sub-sequence starting with the free fall of the climber, identified by searching for a minimum in the resultant acceleration. The end of the sequence is defined by the maximum acceleration. This results in varying sequence lengths.

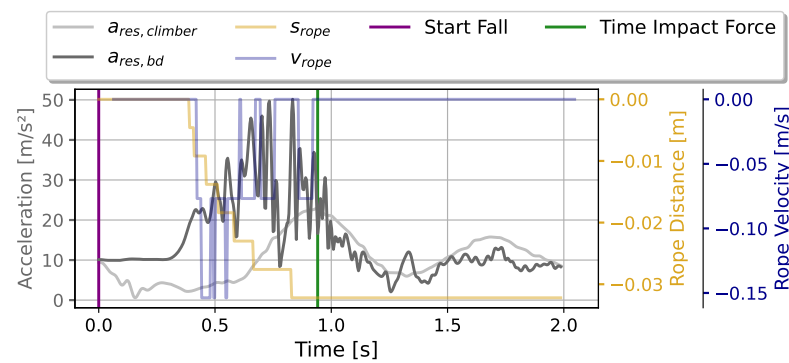


Figure 2. Example of a fall with 0.5 m of slack in the system and a non-dynamic belayer. The timestamp of the impact force (green) and the start time (purple) are marked by vertical lines.

2.3. Feature Engineering

From the resulting acceleration measurements, we manually extracted the features in order to handle the classification and regression task. Each of the features is listed in Table 1. Overall, we extracted 22 features; 11 in the time domain, 10 in the frequency domain, and one in the time–frequency domain.

Table 1. Manually extracted features from the resulting acceleration of the belay device. They are separated by time, frequency, and time–frequency domain features.

Time Domain	Frequency Domain	Time–Frequency Domain
Absolute Energy	Cross Power Spectral Density (Coefficient 2)	Continuous Wavelet Transform Coefficients for the Ricker Wavelet
Absolute Sum of Changes	Absolute Value (Coefficient 0)	
Median	Absolute Value (Coefficient 1)	
Count Above Mean	Absolute Value (Coefficient 2)	
Standard Deviation	Centroid	
Kurtosis	Variance	
Sample Entropy	Skew	
Benford Correlation	Kurtosis	
Absolute Maximum	Fourier Entropy (Bins of 2)	
Autocorrelation (lag of 3)	Fourier Entropy (Bins of 5)	
Autocorrelation (lag of 5)		

2.4. Predictive Analysis

Before using the manually extracted features as inputs for the classifier or regressor, they were scaled using a standard scaler. A neural network could be considered to handle the varying sequence length of the recorded falls. However, due to the relatively small sample size, we opted for a support vector machine instead of a deep learning approach. Additionally, we trained the support vector machine using the leave-one-out approach. This means the test set consisted of a single sample, while the remaining dataset formed the training set. The support vector machine was built with a radial basis function kernel, utilizing a scaled gamma factor and a regularization parameter set to 10.

3. Results

The results are separated into three subsections. The fall sequences are analyzed in Section 3.1, where we compare the different fall configurations in conjunction with the type of belaying. In Section 3.2, the classification results between dynamic and non-dynamic belaying are presented. Finally, we provide an analysis of the estimation of the impact force in Section 3.3.

3.1. Sequence Analysis

The idea behind dynamic belaying is for the belayer to absorb part of the energy acting on the climber during a fall, thereby reducing its severity. The results of our recordings are visualized in Figure 3. Each curve within the slopes represents the average of the resulting accelerations per configuration, while the slopes around the respective sequences represent their standard deviation.

The purple curves represent the resulting acceleration of the climber during non-dynamic belaying. The maximum acceleration, as well as its timing, occurs earlier when belaying dynamically compared to non-dynamic belaying. With dynamic belaying, we were able to reduce the impact force by up to 340.29 N. On average, dynamic belaying also delayed the timing of the impact force by up to 0.129 s. The average results, including their respective standard deviations, for the timing and values of the impact force are shown in Table 2.

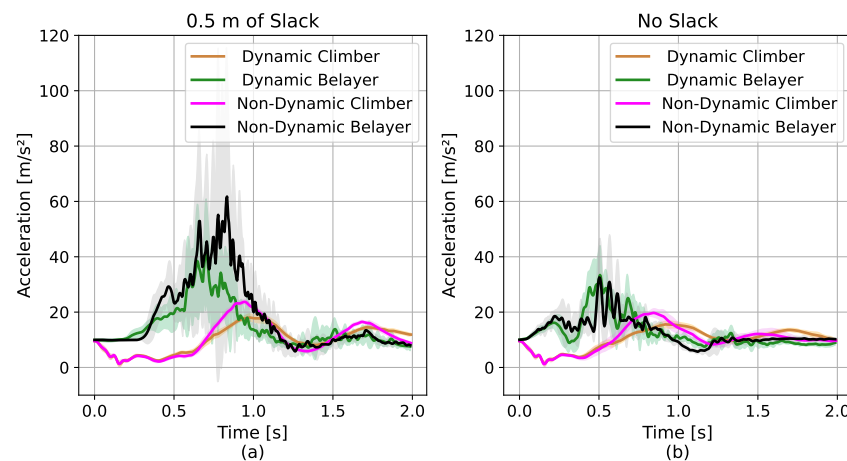


Figure 3. Visualization of the two fall configurations—slack of 0.5 m (a) and no slack (b). Each subgraph displays a summary of the resulting accelerations, once from dynamic and once from non-dynamic belayed falls. The lines highlighted in the legend represent the average over all of the recordings for each configuration. The slope around the curves represent the standard deviation.

Table 2. The registered impact forces and their corresponding time of occurrence separated by the fall configurations.

Configuration	Timing [s]	Impact Force [N]
Dynamic No Slack	0.960 ± 0.053	943.5 ± 70.7
Non-dynamic No Slack	0.831 ± 0.041	1214.2 ± 79.6
Dynamic 0.5 m Slack	0.967 ± 0.047	1104.1 ± 70.2
Non-dynamic 0.5 m Slack	0.921 ± 0.029	1444.4 ± 48.3

3.2. Classification Result of the Type of Belaying

The severity of a fall can be influenced by the type of belaying used—either dynamic or non-dynamic belaying. So, based on the classifier described in Section 2.4 and the engineered feature space from the resulting accelerations measured in the belay device from Section 2.3, we achieved a classification accuracy of 93.18%, with only three sequences falsely classified. Each of these sequences was from the non-dynamic belay class—two without slack and one with slack.

The results from the permutation feature importance are shown in Figure 4. It indicates that the sample entropy from the resulting acceleration has the highest importance in differentiating the type of belaying in a fall situation. Interestingly, only 7 out of the 24 features have a positive impact on the classification task. When reducing the feature space to these seven, the classification accuracy decreased to 88.64%.

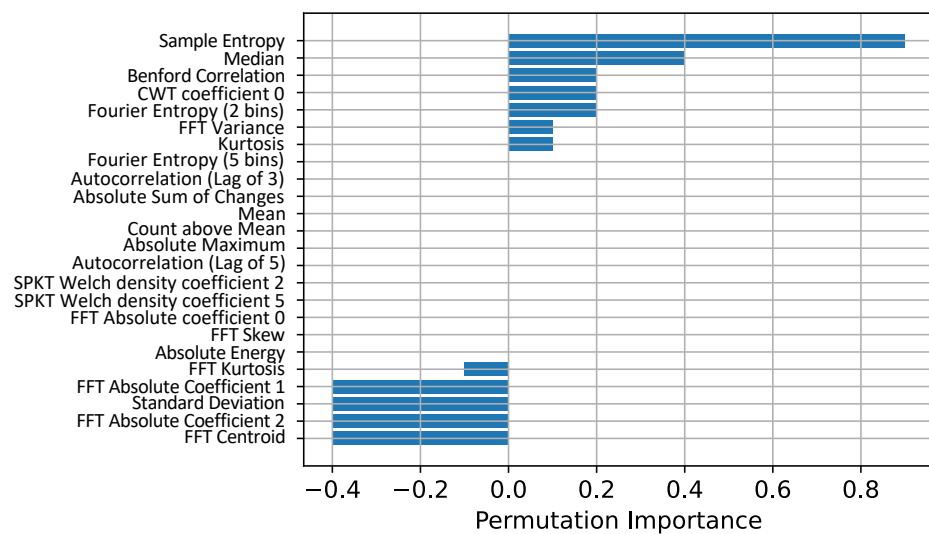


Figure 4. Feature importance based on the permutation feature importance from the classification results using a support vector machine.

3.3. Estimation of the Impact Force

The impact force serves as an indicator of the severity of a climber's fall into the rope. Using a support vector machine, we estimated the force from the sensor information of the belay device alone. The results are visualized in Figure 5. On average, the regressor was able to estimate the impact force with a deviation of (68.74 ± 53.62) N. The maximum deviation was 183.88 N, which represents a deviation of 17.38%pt. However, on average, the deviation in percentage terms from the actual values is around $(0.3 \pm 7.3)\%$ pt.

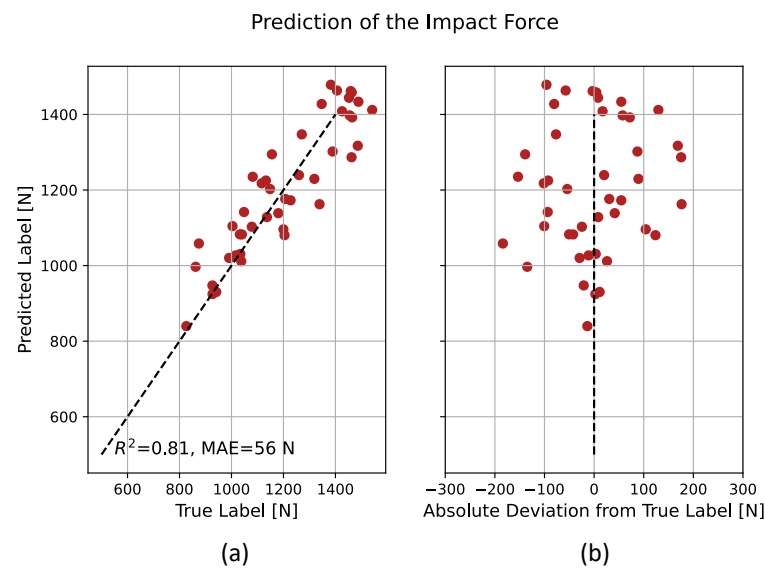


Figure 5. Visualization of the regression results using a support vector machine and manually extraced features. Subfigure (a) visualizes predicted label over the true label, whereas subfigure (b) shows the predicted label over the absolute deviation from the true label.

4. Discussion

Sport climbing is a partner sport, where the belayer and climber have an influence on the severity of the fall. In this study, we investigated the influence of the belayer when a climber falls into the rope. In such situations, the belayer can either use dynamic or non-dynamic belaying. We additionally explored two different configurations—without slack and with 0.5 m of slack. For each configuration, the effect of dynamic belaying could be clearly seen. The belayer was able to reduce the impact force, thereby softening the fall.

We achieved a classification accuracy of 93.18%, with only three sequences being misclassified. However, this result only demonstrates the potential of separating the two classes using a support vector machine, given the limited number of samples and varying configurations that represent a small subset of real-world scenarios. More configurations have to be recorded and analyzed, and adjustments to the friction within the system are necessary. Similarly, for the estimation of the impact force, despite the sparse sample space, we achieved an average error of 0.3%. This underscores the potential of using a belay device to accurately estimate the severity of a fall.

The analysis of feature importance indicated that seven features were the most relevant to the classifier. However, by reducing the feature space to these features, the accuracy decreased to 88.64%. One difficulty is likely the limited number of samples, which hinders generalization. For future studies, expanding the database is essential to improve robustness and generalize findings.

5. Summary and Conclusions

An instrumented belay device can support the sport climbing by providing information in typical climbing situations. This information can then be analyzed and used as a feedback system. In this study, we recorded a climber's fall into the rope and analyzed the severity of the fall based on specific belay behavior. We examined two pre-defined movement patterns—dynamic and non-dynamic belaying. In dynamic belaying, energy is absorbed by the belayer if a climber falls. We were able to differentiate those two movement patterns with an accuracy of 93.18%. The corresponding permutation feature importance identified seven features as relevant for the classification task. Thus, re-training of the classifier using the seven chosen features reduced the accuracy by 4.54%.

Another important indication of the severity of the fall is the impact force. This is defined as the greatest force acting on the climber during a fall into the rope. In order

to estimate this value, we trained the support vector machine using manually extracted features. We found an average deviation of 0.3%pt. However, we still had an outlier with a deviation of over 15%pt, leading to discrepancies of almost 200 N.

The sparse feature space does not allow for a generalized assumption about the results. However, the classifier and regressor returned promising results when estimating the severity of a climber's fall. This information can be utilized in a teaching environment to train belayers and raise awareness about the severity of a climber's fall, especially to demonstrate the impact of dynamic belaying compared to non-dynamic belaying. In our case, the climber was about 20 kg lighter than the belayer and we recorded falls with a fall height of up to 0.5 m. Changing the weight difference between the belayer and climber, as well as increasing the fall distance, further influenced the impact force and demonstrates the necessity for dynamic belaying even more effectively. Such investigations could be conducted in future studies using the instrumented belay device.

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