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Automated Sensor-Fusion Based Emergency Rescue for Remote and Extreme Sport Activities*

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***Abstract*—Even though technological advances changed and improved our daily life in various ways, the risks and dangers of extreme sport activities (ESAs) still persist and the progress of technology had little impact on them. Existing emergency rescue devices for ESAs still require manual activation and do not detect emergency situations autonomously. However, fusing the data feeds of simple sensors can easily enhance the functionalities of those devices and allow for the detection of emergency situations and subsequent rescue in the case of injuries. We identify the difficulties and challenges posed by ESAs, the role and potential value of information technology in such activities and example use cases and scenarios. We further present a prototype device for climbers that can detect potentially dangerous fall events.**

***Index Terms*—Sensor-fusion, extreme sports, rescue system, fall detector, barometer**

I. Introduction

The recent death of rock climber, alpinist and mountaineer Ueli Steck [7] near Mount Everest is one of the latest reminders of the dangers and risks of remote and extreme sports pursued by athletes around the world. Cohen [2] defines extreme sport as "a competitive (comparison or self-evaluative) activity within which the participant is subjected to natural or unusual physical and mental challenges such as speed, height, depth or natural forces and where fast and accurate cognitive perceptual processing may be required for a successful outcome." Further definitions focus on potential dangers and risks of extreme sports and define them as follows: "Any sport or recreational activity that is dangerous and, if performed optimally, even by the highly skilled, risks loss of life or limb." [12] Skydiving, BASE jumping (jumping with a parachute from **B**uildings, **A**ntennas, **S**pans (bridges) and **E**arth (e.g. cliffs)), wingsuit flying, high-altitude mountaineering, free solo climbing (climbing without a rope), cave diving and whitewater kayaking are only a few examples of such activities. Despite the risks and dangers of extreme sport activities (ESAs), as well as the high mortality rate, the number of athletes participating in these kind of activities is increasing over the years–for example, in spite of the high number of deaths on Mount Everest in recent years, the number of ascents of earth's highest mountain (8848 m) has increased almost every year [9]. In 2017, a record number of permits were issued to mountaineers that aim to scale Mount Everest [8].

Limiting and controlling risks as well as providing support in case of emergencies are among the key concerns for conducting extreme sports. Even though the technological advances of the last decades changed and improved our daily lives in various ways, the risks and dangers of extreme sports still persist and pose challenges to even advanced technologies [11], [22]. The harsh conditions and remote locations of extreme sports result in high requirements for the hardware. The lack of easy access to power, as well as extreme temperatures, humidity, altitude and socio-technical limitations impede the design of hardware devices for extreme sports. Despite those difficulties, some devices do provide different types of support to athletes, e.g, satellite phones, avalanche transceiver or satellite emergency notification devices (SENDs) such as the SPOT Gen3 [24], but compared to today's high-tech devices in our daily lives, their capabilities are very limited.

Using sensors and sensor-fusion to monitor the activities of athletes can help to detect (potential) emergency situations and/or accidents, as well as sending automated emergency calls in case the athlete is unable to do so. In the context of ESAs, building such devices is still considered an open issue. Our work addresses the issue of supporting extreme sports athletes during climbing activities. In the course of investigating this issue, we identify the necessary technical requirements and finally develop and evaluate a practical proof of concept solution for detecting potentially dangerous falls of climbers.

The remainder of this work is structured as follows: Section II introduces related works. Following that, Section III focuses on the difficulties and challenges posed by ESAs, the role and potential value of information technology in such activities as well as example use cases and scenarios that are then used to derive technical requirements and functionalities of emergency devices for ESAs. Section IV describes the technical requirements and introduces our prototype implementation of an emergency fall detection device for climbers. Afterwards, an evaluation of the prototype is presented in Section V. In the same section, we also discuss potential enhancements of the prototype for broader applications. Finally, Section VI concludes this work and provides an outlook on future research.

II. Related Work

Over the last years, sensor-fusion based activity recognition (e.g. [16], [30], [31]) is in the focus of research. It is commonly combined with alarm-systems for elderly people (e.g. [4], [15],

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[23]) in order to support their daily lives and to assist them in the case of emergency situations.

For example, Pansiot et al.[16] show that wearable sensors can effectively measure the activity of patients despite ambiguities in the sensor data, by leveraging sensor-fusion techniques. Hong et al.[4] identify different body states (running, sitting, lying, etc.) with high accuracy by using information from accelerometers and RFID sensors. However, these works generally do not consider the use of sensor-fusion based approaches in the context of supporting athletes in the course of ESA activities.

In 2016, Mueller and Pell [13] investigate the role of existing technologies in the context of adventures and certain sport activities.

In the same year, Tonoli et al. [28] propose a wearable device with a Kalman filter-based method to identify falls in the context of climbing activities. However, they exclusively focus on post-processing data instead of instant fall detection. In addition, they solely designed their device to act as a documentarian, disregarding other uses such automatically notifying emergency services. While they attempt to identify falls while climbing, their aim is not to identify potentially dangerous emergency situations. No other types of ESA activities are discussed by the authors.

III. Dimensions and Roles of Technology in ESAs

Understanding the different dimensions and roles of any kind of physical activities supports the proper design and development of new hardware devices for extreme sport athletes. For this purpose, we utilize Mueller and Pell's [13] two dimensional categorization of roles in adventure technology. Based on [17], [25] and in accordance with [1] and [6], Mueller and Pell define adventure as an "exciting experience involving hazardous action with uncertain outcomes based around physical exertion in a natural environment" [13]. Furthermore, they define adventure technology as "technologies that aim to support the adventure, whether they were designed for the adventure or not (for example, adventurers might choose to use high-end smartphones for their expeditions although they are designed for corporate work, often resulting in devastating consequences when they break or lose connection)" [13]. Note that Mueller and Pell's definition of adventure is slightly different from the definition of extreme sports introduced earlier in Section I. If we exclude Mueller and Pell's constraint of the *natural environment*, we come to the insight that in context of this work adventures are an essential part of ESAs–even though the opposite is not true. As a result, we argue that adventure technologies as defined above do not only support adventures but can also be used to support ESAs. Therefore the two dimensional categorization of roles in adventure technology can also be used for technology supporting ESAs.

A. Dimensions of Technology in Adventures

As illustrated in Figure 1, the first dimension relates to the instrumental and experiential aspects of adventure, whereas the second dimension focuses on the expected and unexpected aspects of adventures.

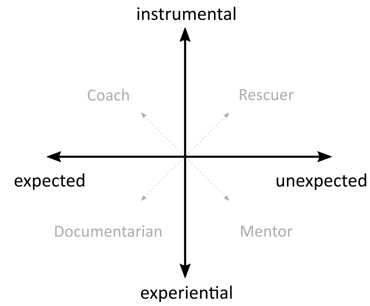

Fig. 1: Four roles adventure technology (Based on: [13])

Instrumental technology helps the athlete or adventurer to achieve tangible goals and improve performance [19], [27]. Typical examples are quantified-self products such as pedometers, Zlagboards [29] for climbers and similar devices.

Experiential technology represents the other end of the first dimension and focuses on technology that supports the adventure experience, such as enabling a deeper engagement with the environment or a richer way of sharing the adventure story [13]. We argue that information and data collected by experiential technology highly valuable for the purpose of planning, logistics and knowledge exchange.

Expected situations are part of every sport activity or adventure and technology supports users in such scenarios, e.g. using a GPS tracker for proper navigation in unknown environments.

Unexpected situations are far more difficult to prepare for by definition and often lead to "using technology for purposes that had not been considered before" [21]. Mueller and Pell describe an example of "hacking" a 2G mobile phone to receive BBC updates about an earthquake by inserting a piece of wire into the audio port of the phone and creating a shortwave magnetic loop around the device to receive BBC Life Line updates via shortwave radio frequencies [13].

B. Roles of Adventure Technology

Based on the two dimensions, Mueller and Pell articulate four roles (coach, rescuer, documentarian, mentor) that technology can play during adventures, as illustrated in Figure 1.

The *coach* technology provides structured guidance in expected situations to improve instrumental aspects, e.g. enhancing performance or providing experience. *Mentor* technology provides the athlete or adventurer with guidance and support for critical reflection, thereby enhancing the adventure's opportunities for personal growth [5].

The technological role of a *documentarian* is most commonly fulfilled by cameras or similar recording devices capturing experiential aspects. The authors mainly focus on self-expression and storytelling aspects, whereas we would like to emphasize less subjective aspects: Using a broad variety of sensor-related devices to capture as many information of the surrounding environment as possible, as well as internal attributes of the user itself. Such data does not only serve as a documentation of achievements, but also provides valuable insights during later analysis that can lead to further performance improvements, risk minimization and avoidance or aids in the planning and logistics of future adventures.

The most crucial role of technology in the context of this paper and the lives of most extreme sport athletes is the role of the *rescuer*. Providing support in case of emergency or having access to emergency services during unexpected situations is a key concern of this work, which aims to minimize the risks of loss of life, limb or any other serious injuries. As mentioned earlier, satellite emergency notification devices (SENDs) such as the SPOT3 [24] already provide basic emergency services by manually pressing an emergency button, but due to the complexity and physical exertion of ESAs, an automated emergency system is able to further minimize risks for extreme sport athletes.

C. *Use-Cases and Scenarios of Technology in ESAs*

As argued above, the presented two dimensional categorization of roles in adventure technology can be applied to technology supporting ESAs in a similar manner. For the purpose of this work, we specifically focus on the application of our approach to climbing and mountaineering in particular due to space constraints. In the following, we map the two dimensional representation system for adventure technology to climbing as an ESA. We focus on the issue of support in case of emergency and how technology can help athletes in such situations.

Since both climbing and mountaineering provide similar use-cases and requirements, we will not further differentiate between the two. Rotillon [20] argues that climbing cannot be considered as an ESA, since everything in climbing is done to eliminate deadly risks. But according to our definitions of extreme sports in Section I, the reduction of risks has nothing to do with the fact of an activity being considered as extreme sport. Most serious injuries in climbing are caused by downfalls of the climber [14]. Injuries can be partially prevented, but downfalls are an essential part of climbing–especially at later stages when pushing personal limits.

Notifying relevant entities about emergencies using the same technique as provided by satellite emergency notification devices (SENDs) is the first crucial part of a *rescuer* system. Devices such as the SPOT3 [24] are capable of sending emergency notifications after manually pressing a button. However, in an emergency, the user may be unable to press a button. The device might be out of reach, or the user could be seriously injured or unconscious and no longer able to press the button. The use of sensor fusion-based techniques for activity recognition enables us to detect emergency situations and automatically send out a emergency notifications. Since not all downfalls are emergencies, the device needs to consider only falls of a certain minimum height (e.g. more than ten meters) or those with following inactivity, which indicates an incapacitated user. In order to avoid false alarms, the device announces the detection of a potentially serious fall by emitting a loud alarm signal. If the user starts moving again, the device recognizes the false alarm and does not send out an emergency notification. Similar approaches are used in order to prevent death by hypothermia or lack of oxygen during high-altitude mountaineering.

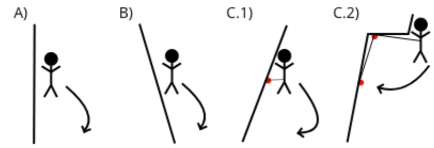

Fig. 2: Different scenarios of fall events in climbing.

IV. Prototype Implementation of an Emergency Fall Detector System for Climbers

Based on the use case analysis conducted in Section III-C, the design and development process of a prototype for downfall detection during climbing activities is outlined in this section.

A. *The Theory of Downfalls*

Downfalls are an essential part of climbing, especially when pushing personal limits. Climbers clip their rope into several carabiners connected with the wall–so called quickdraws–while climbing in order to keep the length of falls to a minimum. However, this is not always possible and in certain situations it is not possible to place such protections at all. In such cases, the distance between two consecutive quickdraws can be quite long or part of the protection fails and therefore extends a downfall significantly. However, a downfall is not only defined by its length. The angle of the climbed wall is another important factor. Some examples for this are given in Figure 2: scenario A shows the case of a vertical wall, B a slightly inclined wall, thereby creating a slab, C.1 and C.2 show walls with an overhang. Depending on the wall's angle, the climbers acceleration during a fall might differ due to friction. In addition, the number of clipped quickdraws and the angle between rope and quickdraws adds further friction, thereby lowering the speed of a fall. Moreover, climbers use dynamic ropes that elongate in case of a downfall. Nowadays climbing ropes elongate between $28\,\%$ to $35\,\%$ (dynamic elongation). Finally, experience and behavior of the belayer, who secures the rope at the ground level, also influence the downfall either in a negative or positive manner. Most downfalls have no consequences at all due to the small fall length (usually less than 2m) and the climber continues climbing almost immediately. More serious falls are rare especially indoors. However outdoors, fall distance might reach up to 10m and pose a serious threat to the climbers health in case of a fall.

B. *Prototype Implementation*

The purpose of implementing this prototype is to demonstrate that a device with minimal hardware and software requirements could save the lives of climbers in case of accidents. The prototype detects serious falls (more than two meters in fall distance) and sends an emergency signal in case the climber does not start moving again afterwards. Since the prototype is supposed to only detect serious falls, extreme accuracy is less relevant which reduces hardware and software requirements.

To automatically detect falls that occur during a climbing session, our hardware device has to be capable of measuring acceleration data. In addition, it is also necessary to determine height differences during sudden movements. For this, we use a barometer to calculate heights. Furthermore, in the context of ESAs the device has to be designed in such a way that it does not prevent the user from properly pursuing her or his activity. We use an Android Nexus 5 phone [3] for our prototype, but a small microcomputer such as a Rasberry Pi [18] with corresponding sensors can also be used as an implementation platform. The smartphone is equipped with an MPU-6515 6-Axis motion sensor, based on the MPU-6500[26], and a barometer as is necessary to collect the relevant data. An Android app is then processing the collected data using a Kalman filter [10] in order to smooth the recorded data before further processing it. The pre-processed data records are analyzed with minimal delay in order to detect relevant acceleration deviations that indicate a downfall. In case the downfall exceeds the pre-defined value for potentially dangerous situations, an alert sound is played. In case the climber does not continue her or his climb at some point after the downfall, a further symbolic emergency notification message is send via the phone. If the climber starts moving again, the emergency notification is canceled and the downfall marked as not harmful. The setup is placed in a small bag and attached to the climber's harness while climbing. The demonstrated prototype does not contain any functionalities to actually send emergency notifications to emergency services.

Android allows the customization of the sensor readout frequency for every sensor. For our purpose, it is necessary to gather sensor data as quickly as possible since fall events may occur at any time. Our prototype uses the fastest readout interval for both the accelerometer and the barometer sensor. The accelerometer is gathering approximately 200 samples per second ($200\,\mathrm{Hz}$), while the barometer is gathering around 30 samples per second ($30\,\mathrm{Hz}$). In the context of most ESAs, electricity is a scarce resource and our prototype application is continuously gathering sensor data in the background. Hence, it is interesting for us to analyze the battery consumption of our application. To do so, we used the profiler of the Android Studio IDE. By comparing the data collected by the profiler we get an overall estimated CPU utilization of $30\,\%$. According to the specification of the accelerometer, we determined that the accelerometer has a normal operating current of $500\,\mu\mathrm{A}$. The power consumption during a seven hour test run of the application on the Nexus 5 phone was around $453\,\mathrm{mA\,h}$.

The barometer monitors the current altitude of the climber and calculates the fall distance. A Kalman filter is used to smooth the altitude outputs. The Kalman gain is determined by calculating the variance of raw barometer samples and adjusting the process variance. The process variance is usually assumed to be very low and was determined experimentally to match the desired filter performance. Our variance of the barometer sensor is 0.010627865 while the desired filter performance is achieved using a process variance of 10^{-6}.

Climber	Gender	Weight	Height	Falls	Belayer
Climber A	male	$81\,\mathrm{kg}$	$183\,\mathrm{cm}$	6	0
Climber B	male	$86\,\mathrm{kg}$	$188\,\mathrm{cm}$	10	1
Climber C	male	$70\,\mathrm{kg}$	$180\,\mathrm{cm}$	6	2
Climber D	female	$74\,\mathrm{kg}$	$175\,\mathrm{cm}$	-	1

TABLE I: Data of test climbers that helped to evaluate the fall detection algorithms.

In order to get more reliable data on fall events that have been detected by our Android application, we decided on implementing two algorithms that were following two similar yet different approaches.

Algorithm A analyses the accelerometer values and Kalman filtered barometer altitudes. Falls are detected whenever the acceleration is close to $0\,\mathrm{m/s^2}$ on every axis. However, the actual free fall condition of $0\,\mathrm{m/s^2}$ on all axes is never achieved in our climbing scenario as the rope is slowing down the fall due to various factors such as friction. Therefore, we set a threshold for the beginning of fall events. We experimentally determine that a threshold of $2\,\mathrm{m/s^2}$ delivers reliable data on detected falls. The end of a fall event is identified by a harsh and rough movement, characterized by sudden amplitudes in the accelerometer values. To obtain the fallen distance, the difference between the barometric heights readings of the beginning and end of a fall event are processed.

Algorithm B only processes raw altitude data from the barometer and compares them in blocks of five samples. For each block, the algorithm keeps track of the minimum and maximum average height of the last five samples compared to the previous blocks average altitude. Whenever the calculated distance between the current highest and lowest average altitude of all blocks exceeds $1.5\,\mathrm{m}$ a fall event is detected and the previous highest and lowest average altitudes are reset.

V. Prototype Evaluation

The following section covers the evaluation of the prototype described in the previous section.

A. Evaluation

We conduct a test series of 22 test falls with 3 different climbers (see Table I) who test our prototype in different fall scenarios (scenario A and scenario B from Figure 2). A fourth climber participates as a belayer in our test sessions. A dynamic rope (Edelrid Harrier) with an elongation of $34\,\%$ is used. We aim for a falling distance of $1.5\,\mathrm{m}$–meaning that the climber has $1.5\,\mathrm{m}$ of rope above the last point of where he/she clips the rope into a quickdraw. Depending on rope elongation, the belayer, who controls the safety rope of the climber, and the weight different between the climbers this results in falls between $1.5\,\mathrm{m}$ and $3.5\,\mathrm{m}$. For safety reasons, all test falls are conducted in an indoor climbing facility and we limit the maximum fall distance to $3.5\,\mathrm{m}$.

During the sessions, the fall detection device is attached to the harness of the climber and records data from the start

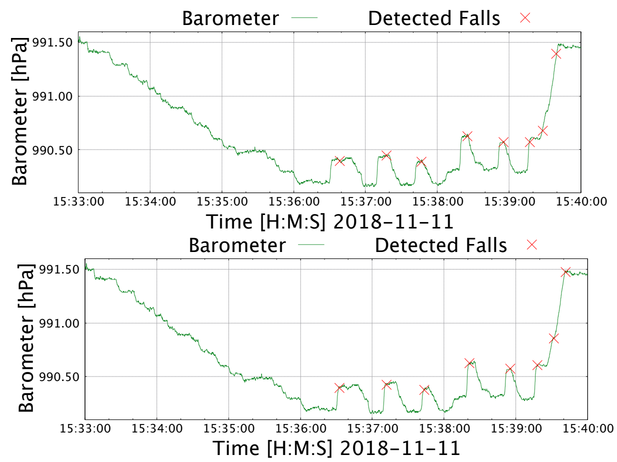

Fig. 3: Test session 1 with climber A conducting 6 falls in scenario B (Algorithm a (top), algorithm b (bottom)).

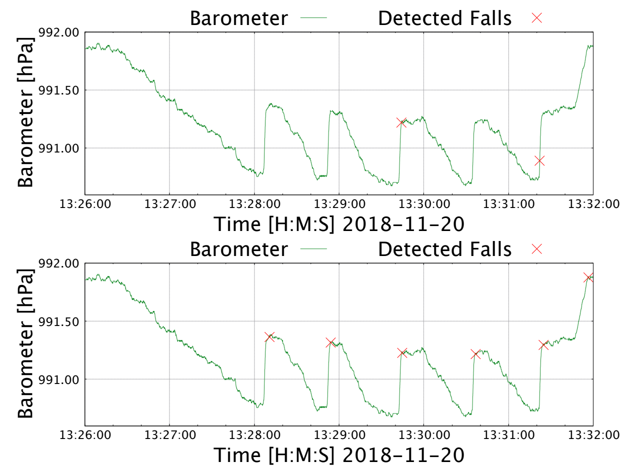

Fig. 4: Test session 2 with climber B conducting 5 falls in scenario A (Algorithm a (top), algorithm b (bottom)).

of each session until the climber is back on the ground. Figure 3 and Figure 4 illustrate the results of two of our four climbing sessions with a total of 22 falls. Session 1 (Figure 3) is conducted on a slightly inclined wall (scenario B), while session 2, 3 and 4 cover scenario A. For each figure, we present the barometer data (y-axis) over time (x-axis); detected falls are marked with red crosses. Note that using the data output from the barometer means that climbing upwards results in a reduced barometric pressure–hence, climbing upwards results in decreasing graph values, while conducting a test fall raises the barometric pressure again due to a loss of height above ground. The collected data is processed with the two fall detection algorithms presented in Section IV-B.

The first test session is conducted with climber A in scenario B and is illustrated in Figure 3. The graph starts at the moment where the climber starts his ascent. At the top of the route, six test falls are conducted. Both algorithms detect all six falls correctly. However, both algorithms also detected the process of lowering the climber to the ground (after the test falls) as false positives. The false positives occur, because our experienced belayers are accustomed to relatively high lowering speeds. However, since the climber does not remain inactive after being lowered, no emergency message is dispatched.

The second test session is conducted with climber B in scenario A and is illustrated in Figure 4. The climber starts his ascent and afterwards conducts five test falls. In contrast to the first test session, algorithm A performs worse than algorithm B and misses three falls resulting in false negatives. Algorithm B performs much better, but once again detects a false positive during the process of lowering the climber at the end of the test session.

Based on the results of the four test sessions, Table II presents the confusion matrix for algorithm A and algorithm B. Algorithm A correctly detects 19 out of 22 falls while missing 3 falls and falsely detecting 6 false positives. On the other hand, algorithm B correctly detects all 22 falls while further detecting 4 false negatives. In the context of ESAs, detecting false positives is a neglectable issue while missing potentially life threatening events can be lethal. By adding a further activity check (i.e. does the climber start moving again just after a detected fall?) before sending an emergency signal, the impact of such false positives is mitigated.

The source code of the Android app and a video of session 3 is available online*.

B. Discussion and Limitations

The authors are aware of the limitations of the small sample set size used to evaluate the accuracy and overall functionality of the proposed prototype. However, due to limited resources and test climbers only a small number of falls can be performed. For the same reason, we also cannot conduct test falls for scenario C. However, C.1) as well as C.2) are–in terms of physical fall properties–closely related to scenario A) and are expected to be detected with a similar accuracy. Moreover, for safety reasons the data sample only contains test falls that occurred indoors. Large falls outdoors can lead to severe injuries due to the height of the fall or other safety hazards. We also limited the maximum fall height of our test sessions to not threaten the safety of our test climbers. Nevertheless, we are confident that the results of our fall detection system will yield similar detection rates for larger and potentially more dangerous falls due to the fact that these are much easier to detect due to the larger fall distances and speed.

Besides the limitations of our evaluation method, the prototype is not yet ready to be deployed in real use scenarios due to certain insufficiencies. Besides finalizing the software component of the prototype, the hardware has to be updated as well. Most ESAs are pursued outdoors and often in remote areas. Hence a small device with long battery runtime as well as a durable casing (e.g. IP68 certified) are necessary. Furthermore, the device has to be resilient against extreme temperatures - both heat and cold. In order to increase accuracy of detected emergency events, future iterations of the prototype might include additional sensors for sensor-fusion based data

*https://www.youtube.com/watch?v=RH1ccpYoTns
https://github.com/bleidingGOE/ESA-climber-fall-detection

	A		B	
	Fall	**No fall**	**Fall**	**No fall**
Detected	19	6	22	4
Not detected	3	many	0	many

TABLE II: Confusion matrix for algorithm A and B.

analysis and even consider monitoring devices such as smart watches in order to ease testing of the system.

VI. Conclusion

Despite the ever growing influence and pervasiveness of technology in our daily life, ESAs have been somehow excluded from the advances in this area. In this work, we propose a sensor-fusion based system for ESAs that allows for the detection of emergency events and subsequent rescue in the case of injuries. We present a prototype for climbers that can detect potentially dangerous fall events.

The prototype correctly detects $100\,\%$ of the conducted 22 test falls successfully while further detecting 4 false positives. In the context of ESAs, detecting false positives is a neglectable issue while missing potentially life threatening events can be lethal. By adding a further activity check (i.e. climber moves again) before sending an emergency signal, the impact of such false positives is mitigated.

In the future, we plan to develop a hardware device that provides sufficient resilience against outside influence (e.g. IP68 certification) with a long battery lifetime and a small casing. Moreover, we plan to add further modules for other ESAs such as skydiving, BASE jumping, mountaineering and whitewater kayaking. Depending on the activity, the user can switch between different modes and configure specific settings. We also plan to employ sensor-fusion methods that improve the number of potential emergency events that can be detected by our device. Moreover, for use in remote areas we plan to add a satellite communication module similar to the SPOT Gen3. Finally, we will add functionalities that extend the use case of the device from the role of the *rescuer* to further roles such as documentarian, mentor and coach.

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