Recognizing turns and other snowboarding activities with a gyroscope

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Recognizing Turns and Other Snowboarding Activities with a Gyroscope

Thomas Holleczek, Jona Schoch, Bert Arnrich, Gerhard Tröster
Wearable Computing Lab.
ETH Zurich
Zurich, Switzerland
hollthom@ethz.ch

Abstract

Wearable sports trainers are built upon sensor systems recognizing the activities performed by its users. In snowboarding, one of the fastest growing sports in the world, traditional activity recognition approaches make use of insoles with integrated force-sensitive resistors. However, such insoles are usually uncomfortable to wear, tedious to calibrate, error-prone and their functionality is limited to the detection of turns. We have therefore developed an alternative snowboarding activity recognition system, which overcomes these downsides. It consists of a mobile computing device with a GPS receiver, and a gyroscope attached to the center of the snowboard. The system is easy to set up, as the gyroscope can be simply taped onto the snowboard without any user-specific calibrations. Experiments with seven riders in three Swiss ski resorts show that our activity recognition system is capable of withstanding harsh conditions on outdoor slopes. It detects turns, the basic elements of snowboarding, independently of user, snowboard, slope and snow characteristics. In addition to the mere detection of turns, our system can reveal whether the snowboarder is riding on the frontside or the backside of the board, whether she is going forwards or backwards and whether she is carving or skidding. Finally, first studies suggest that gyroscope-based activity recognition can also be applied to snowboarding-like sports such as skiing and skateboarding.

1 Introduction

Snowboarding is a popular winter sport, which originated in the United States in the late 1960s and early 1970s. Borrowing techniques and tricks from both surfing and skateboarding, snowboarding is often described as *surfing on snow*. Snowboarders ride down slopes covered with snow by standing sideways on a lightweight board of about 160 cm in size, which is attached to their feet. Like in skiing, the key concept to descend is to manipulate gravity and perform turns across the fall line. However, unlike skiers, who shift their weight from one ski to the other, snowboarders move their weight from the heels to the toes and vice versa. Riders may stop the motion of the board by pushing heels or toes down hard to dig the edge of the snowboard into the snow. Improving one's skills in a sport such as snowboarding, which requires complex motion sequences and perfect balance, is often only possible through expensive lessons (in Switzerland currently around 100 US$ per hour) given by an experienced teacher [1]. Yet even this approach has its limitations, as instructors might not notice all mistakes. We have therefore been developing a wearable sensor-based assistant, which is capable of analyzing the movements and motions of snowboarders automatically and supports them in improving their riding style. On our way to a wearable snowboarding trainer, we demonstrate how a gyroscope can be used to detect turns and nine other snowboarding activities.

The organization of this paper is as follows. Section 2 reviews the start of the art of related works in snow sports. Section 3 briefly explains the basics of the snowboarding domain. Section 4 describes the design of our activity recognition system. Section 5 introduces algorithms required for gyroscope-based activity recognition in the snowboarding domain. Finally, Section 6 shows the results of real-life experiments with our system conducted on outdoor ski slopes in the Swiss ski resorts Braunwald, Savognin and Grindelwald.

2 State of the Art

There are a couple of research projects concerned with the development of wearable assistants in snow sports. One of the first projects deals with the monitoring of professional downhill skiers. It aims at revealing information about the skiers' motions and helping teachers identify their strengths and weaknesses [2]. In ski jumping, taking off is the most important phase as it influences the overall performance. Le Challenec [3] analyzes the take-off phase with body mounted inertial sensors. Another project deals with automatic scoring in half-pipe snowboarding competitions [4]. Its goal is the development of a sensor system capable of automatically detecting objective scoring criteria such as the average time spent in the air and the number rotations of the contestants and thereby allowing the judges to focus on subjective style criteria.

Usually, the basis of a wearable sports trainer is a sensor system recognizing the activities performed by its user. In a second step, the segmented activities are evaluated regarding specific quality measures. Finally, a feedback component informs the user (in real-time or after the workout) about her performance and supports her during the learning process. The idea of a wearable snowboarding trainer was first brought up by Spelmezan [5], who envisions a wearable system capable of recognizing common beginners' mistakes such as a wrong weight distribution inside the boots, wrong postures and incorrect rotations of the upper body, and insufficient knee flexion. Whenever the wearable trainer detects one of these mistakes, a vibrotactile feedback component notifies the user. As a first step, a preliminary activity recognition system was developed by [5], which, however, is limited to the detection of turns, the basic activity of snowboarding. The prototype is based on a pair of insoles integrating force-sensitive resistors (FSRs), which measure the pressure at various positions inside the boots. The analysis of the pressure sensor data with a thresholding approach allows for the detection of turns on well prepared indoor ski slopes with an accuracy of 98 %. Equivalent results are achieved by Holleczek and Schoch [6], [7], who have developed a robust activity recognition system with pressure insoles for use on outdoor ski slopes. However, using pressure insoles as a basis for the recognition of snowboarding activities entails a long list of drawbacks. First of all, test subjects regularly complain they are uncomfortable to wear as the snowboarding boots are already tight-fitting without an extra pair of insoles. Having to be calibrated individually for each snowboarder, the pressure insoles require setup times in the range of half an hour. Moreover, they cannot be adjusted to different shoe sizes and prove to be especially error-prone once the temperature drops below $-15\,°C$ [7], which is common for outdoor ski slopes. Finally, it is infeasible to infer from the measured pressure whether the board is ridden forwards or backwards and which turning technique snowboarders apply.

3 Snowboarding: Terms and Overview

This section is dedicated to a short introduction to the snowboarding domain. It is mainly based on the standard Swiss textbook about snowboarding of the [1].

3.1 Gear

The basic hardware required for snowboarding consists of a snowboard and a set of bindings attached to it. A **snowboard** is a lightweight board of around 160 cm in size with two long edges. The one on the side of the heels is referred to as *backside*, the other one on the side of the toes is called *frontside*. The front end of the snowboard is referred to as *nose*, the back end as *tail*. Snowboarders stand sideways on the board. We can distinguish two types of stance directions for snowboarders. *Regular* riders have their left foot at the front of the board, whereas *goofy* refers to the opposite stance direction, i.e. the right foot is at the front. The snowboard in Figure 1 is adjusted for a goofy rider. **Bindings** are separate components and attached to the snowboard with several screws. Their main function is to hold the rider's boots in place tightly to allow her to transfer energy to the snowboard.

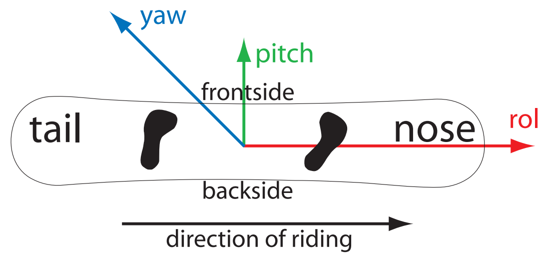


Figure 1. Snowboarders stand sideways on the board. The backside of the board is the edge on the side of the heels, the frontside is the one on the side of the toes. The front end of the snowboard is referred to as nose, the back end as tail. Here, the right foot is at the front of the board, which means the stance is goofy. The red arrow represents the roll axis, the green arrow stands for the pitch axis and the blue one for the yaw axis of the snowboard

3.2 Snowboarding Model

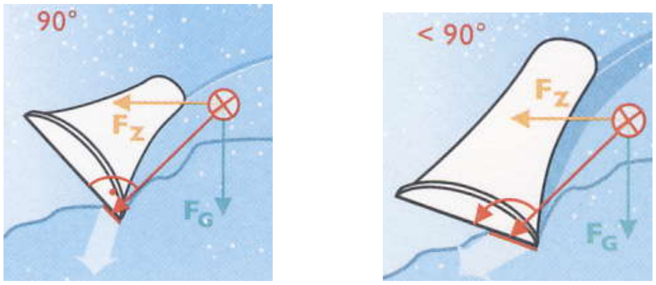
Holleczek [6] introduced a simple snowboarding model, which regards the descent of a snowboarder as a sequence of alternating turns. In accordance with Primus [1], we have developed an extended model, which also takes into account the fact snowboarders may ride forwards or backwards and use different techniques. At any time during the descent, the state of a snowboarder can be described by the tuple [Action, Edge, Direction, Technique].

Action: A snowboarder is either inactive (halting) or active (moving).

Edge: The edge indicates the side of the snowboard being in use. Snowboarders use either the *backside* or the *frontside* of their board.

Direction: The direction refers to the riding direction of the snowboard. Boarding *normally* stands for riding the snowboard in its natural direction. That is, regular riders have their left foot in front and goofy riders their right one. Boarding *switch* means riding the snowboard backwards. A goofy rider boarding switch looks like a regular rider boarding normally and vice versa, except that the tail of the snowboard would be leading the way. Since switch boarding means using the other foot as the leading foot, it is a lot harder for most riders than boarding normally.

Technique: An active, riding snowboarder is either carving or skidding (see Figure 2). *Carving* describes the movement of the snowboard on the snow where the direction



(a) Carving. The direction of the movement is exclusively parallel to the board

(b) Skidding. The motion of the snowboard also contains a component of movement to the side

Figure 2. Snowboarding techniques: A riding snowboarder is either carving or skidding [1]

of motion is exclusively parallel to the board, as shown in Figure 2(a). To make this happen, the pressure applied to the snowboard must be perpendicular to its lateral axis. A snowboarder can ride on either the frontside or backside edge of the snowboard. Carving is considered to be the most elegant way of descending on slopes. *Skidding* refers to the situation when the motion of the snowboard contains a component of movement to the side, which is illustrated in Figure 2(b). This happens when the generated pressure of the snowboard is not perpendicular to the snow. The percentage of the component of movement to the side may vary from very small, when performing a wide turn, to very high, when skidding down the hill with the board perpendicular to the fall line. Snowboarders skid either on the frontside or the backside of their boards. Being easier to perform than carving, the skidding technique is usually applied by beginners of snowboarding.

A **turn** is an event describing a state transition in the snowboarding model, when the used edge or the direction changes. During a turn, the movement of the snowboard describes a circular path. Two different turns are possible, and they are named after the side of the board on which the turn is ridden, i.e. the side facing the inside of the turn. If the rider initiates the turn from the backside towards the frontside, we speak of a *frontside turn*. Otherwise, the turn is called a *backside turn*. Turns can be either carved or skidded and involve a rotation of the board along its roll and yaw axis as illustrated in Figure 3.

The states and state transitions of our snowboarding model are summarized in Figure 4. The model itself is shown formally as an hierarchical UML state diagram in Figure 5 and is illustrated in Figure 6 [1].

4 System Design

The motions of the snowboard and the snowboarder on the slope are captured by an inertial measurement unit (IMU)

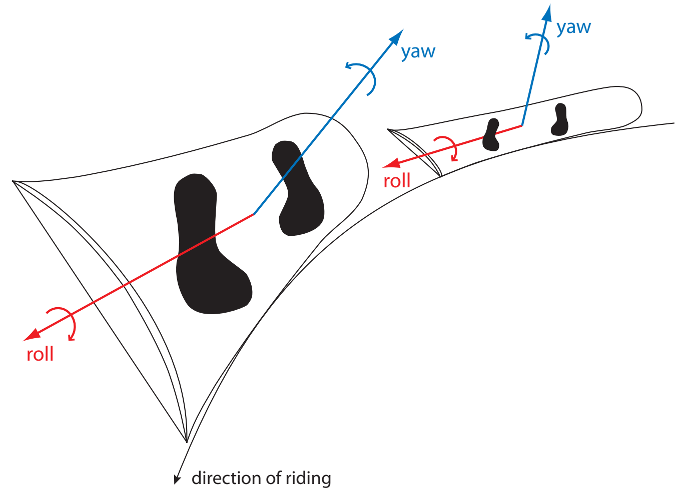


Figure 3. Normal frontside turn of a goofy rider. The turn involves a rotation along the roll and yaw axis of the snowboard

Category	States	Snowboarder ...
Action	Inactive	halts
	Active	rides
Edge	BS	rides on frontside edge
	FS	rides bon frontside edge
Direction	Normal	boards in natural stance
	Switch	boards in unnatural stance
Technique	Carving	carves
	Skidding	skids
	Riding	either carves or skids
Turn	NO BS	performs normal backside turn
	NO FS	performs normal frontside turn
	SW BS	performs switch backside turn
	SW FS	performs switch frontside turn

Figure 4. States of the snowboarding model. A snowboarder is either inactive or active [active, (backside/frontside), (normal/switch), (carving/skidding)]. State transitions are described by four different types of turns

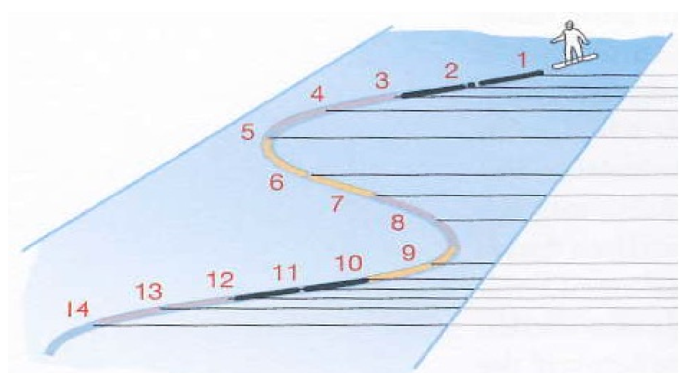


Figure 6. Illustration of the snowboarding model at the example of a goofy rider. The snowboarder starts riding on the backside at (1), heading right. At (5), he performs a frontside turn and switches to frontside riding, which is followed by a backside turn at (9) etc. [1]

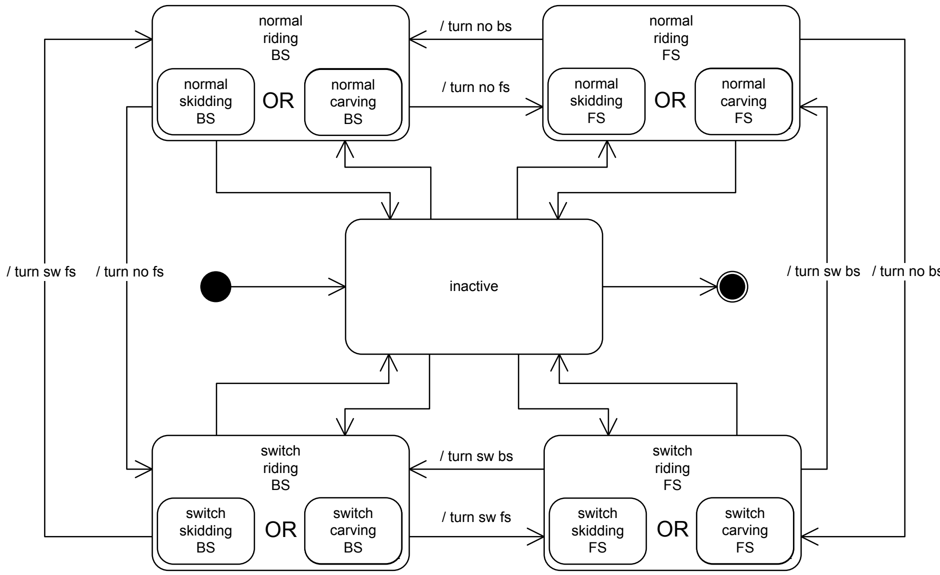


Figure 5. Full snowboarding model as an hierarchical UML state diagram. A snowboarder is either halting (inactive) or moving [active, (backside/frontside), (normal/switch), (carving/skidding)]. The filled circle represents the initial state, the hollow circle containing a smaller filled circle indicates the final state of a descent. A snowboarder starts her descent by riding either normally or switch. The descent itself consists of a series of backside and frontside turns during which the direction of travel may be changed. Between turns, the snowboarder is either carving or skidding

(a) Board IMU (b) Packaged Board IMU

Figure 7. Board IMU featuring a two-axial gyroscope, a tri-axial accelerometer and a Bluetooth module for wireless data transmission

and a GPS receiver. The core of the sensor system is a mobile computing device, which records and later analyzes the sensor data.

Board IMU: As shown in Section 3, turns are based on rotations along the roll and yaw axis of the board. We decided to monitor these with an IMU, which was designed and built in-house. It features a two-axial gyroscope, a tri-axial accelerometer ($-3\,\mathrm{g}$ to $3\,\mathrm{g}$), and a Bluetooth module for wireless transmission (see Figure 7). The IMU uses a sampling frequency of 32 Hz. The packaged Board IMU is taped onto the center of the snowboard such that the gyroscope measures the rotation along the roll and the yaw axis.

GPS receiver: The task of the GPS receiver is to track the movements of the snowboarder. Being the best trade-off between low cost and sufficient accuracy of lateral CEP (Circular Error Probable), we selected the device *Wintec WBT-300* with a localization update rate of 10 Hz, and CEP of 3 m for localization and $0.1\,\mathrm{m\,s^{-1}}$ for speed estimation.

Mobile computing device: The Board IMU and the GPS receiver maintain a Bluetooth connection to an ASUS Eee PC 1000H with a solid-state disk placed in the backpack of the test rider. The sensor data are captured by the CRN Toolbox [8] running on the netbook. After the snowboarder has completed a descent, activity recognition algorithms analyze the recorded data offline.

5 Activity Recognition

In general, activity recognition aims at determining activities from a series of sensor observations, usually for the sake of providing additional support to humans. In our case, knowledge of the snowboarder's activity at any time during the descent is required for the evaluation of her performance. Our activity recognition system is dedicated to automating this task after the completion of descents: it determines the riding state at any time during the run using classification techniques. The goal of classification is to assign data points to that class of a set of well-defined classes by which it was most likely generated. In our case, the classes are all the states from the snowboarding model, which means there are nine classes to distinguish (see Figure 5). We decided to follow a continuous activity recognition approach as Minnen

[9] to ship around an explicit segmentation of the sensor data. That is, start and end points of activities do not have to be known as they are detected implicitly. To keep our first activity recognition prototype fast and simple, we further decided to go for rather basic recognition algorithms. In a first step, the segments of the run have to be identified when the snowboarder is moving (Section 5.1). These parts are then further partitioned into subsegments through a turn detection algorithm (Section 5.2), i.e. the state transitions are determined. Finally, the activities happening inside the identified subsegments are classified with respect to the used edge (Section 5.3), direction (Section 5.4) and technique (Section 5.5).

5.1 Action Detection

To recognize when a snowboarder is active or inactive, the action detection algorithm analyzes either the speed delivered by the GPS receiver or the gyroscope data of the yaw axis from the Board IMU. This enables an action detection even if the GPS signal is not reliable, e.g. on a slope where the signal is obstructed by trees. The action detection algorithm uses a sliding window approach and threshold values for both the GPS and gyroscope data. Once the average of the data inside a window exceeds a threshold value, the snowboarder is assumed to be *active*. Otherwise, the classification result of the action detection algorithm is *inactive*. The algorithm is illustrated in Figure 8.

5.2 Turn Detection

The detection of turns is performed on the gyroscope data recorded by the Board IMU in the segments when the snowboarder is active. A turn mainly consists of a rotation around the roll and the yaw axis of the snowboard, which is illustrated in Figure 3. This rotation is captured by the gyroscope of the Board IMU and shows up as peaks in the sensor data. To detect turns, our algorithm therefore applies the peak detection from Algorithm 1 to the sensor data. A peak in the roll axis can be regarded as the moment when the snowboard turns from one edge to the other. To classify the turn as a frontside or backside turn, the stance of the snowboarder has to be known. As the tilt of the snowboard towards an edge is the same irrespective of the riding direction, the rotation along the roll axis is the same for a normal backside turn and a switch backside turn. This is not the case for the rotation around the yaw axis. The rotation around the yaw axis in a normal backside turn is exactly opposite to the rotation around the yaw axis in a switch backside turn. The algorithm therefore selects the peak in the yaw axis which is closest to the one in the roll axis. From these two peaks, the turn (backside or frontside) and the direction (normal or switch) can be determined, as long as the stance (regular or goofy) of the snowboarder is

Algorithm 1 detectPeaks(x, δ, b)

Require: x data array
Require: δ minimal vertical distance between two peaks
Require: b band in which peaks should be ignored
max $= -\infty$
min $= \infty$
for all $x_i \in x$ **do**
  if $x_i >$ max **then**
    max $= x_i$
  else if $x_i <$ *min* **then**
    min $= x_i$
  end if
  if $x_i <$ *max*$-\delta$ **then**
    add *max* to *maxpeaks*
    max $= x_i$
  else if $x_i >$ *min*$+\delta$ **then**
    add *min* to *minpeaks*
    min $= x_i$
  end if
end for
remove all elements from *maxpeaks* and *minpeaks* in b
return *maxpeaks* and *minpeaks*

Roll axis	Yaw axis	Stance	Mode	Edge
min peak	max peak	Regular	NO	FS
		Goofy	NO	BS
max peak	min peak	Regular	NO	BS
		Goofy	NO	FS
min peak	min peak	Regular	SW	FS
		Goofy	SW	BS
max peak	max peak	Regular	SW	BS
		Goofy	SW	FS

Figure 9. Type of turn depending on type of identified peaks on roll and yaw axis, and the stance of the snowboarder

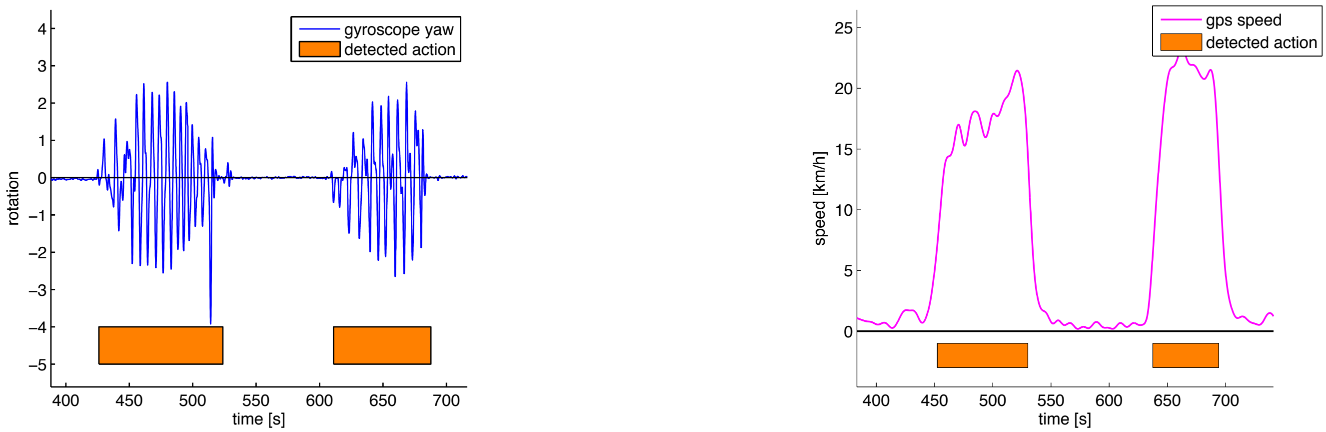
known. Figure 9 shows this relationship. The algorithm for turn detection is formalized in Algorithm 2. An example for the turn detection algorithm is presented in Figure 10.

5.3 Edge Detection

The riding edge can be derived directly from the detected turns. A rider performing a normal or switch frontside turn will be riding on the frontside edge of the snowboard when leaving the turn. The opposite is true for a normal or switch backside turn, where she will be boarding on the backside edge thereafter. To determine the edge between the start of a ride and the first turn, the counterpart of the edge of the first turn is taken, e.g. if the first turn is a frontside one, the edge up to this turn is considered to be backside. This implies that the used edge cannot be detected until a turn has happened.

5.4 Direction Detection

The direction detection is similar to the detection of the used edge. When a rider has performed a normal frontside



(a) Board IMU

(b) GPS

Figure 8. Action detection based on Board IMU in Figure 8(a) and GPS receiver in Figure 8(b). The sensor data are processed with a sliding window approach. Once the average of the data inside a window exceeds a threshold value, the snowboarder is assumed to be *active*. Otherwise, the classification result of the action detection algorithm is *inactive*

Algorithm 2 detectTurns(r, y, δ, b)

Require: r gyro data of roll axis
Require: y gyro data of yaw axis
$[maxpeaks_r, minpeaks_r] = \text{detectPeaks}(r, \delta, b)$
$[maxpeaks_y, minpeaks_y] = \text{detectPeaks}(y, \delta, b)$
for all $x \in maxpeaks_r \cup minpeaks_r$ **do**
  find peak $z \in maxpeaks_y \cup minpeaks_y$ closest to x
  determine direction and edge of turn $t = [x, z]$ acc. to Figure 9
  add t to *turns*
end for
return *turns*

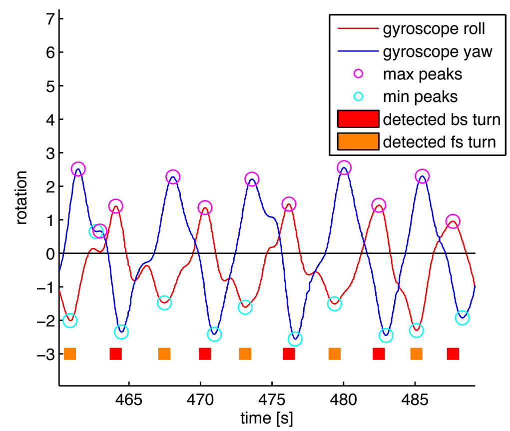


Figure 10. Turn detection for a regular rider. First, Algorithm 1 identifies all peaks on the roll and yaw axis. For each peak on the roll axis, the nearest peak on the yaw axis is determined. Based on the combination of peaks, the type of the turn is determined according to Figure 9

or backside turn, she must be riding in normal direction after the turn. A turn ridden switch implies that the rider is boarding switch afterwards. The direction between the beginning of a ride and the first turn is determined by the first turn. As for the edge detection, the direction cannot be detected until a turn has happened.

5.5 Technique Detection

Detecting whether the snowboarder is carving or skidding happens between two detected consecutive turns. When skidding, the flight of the snowboard is much bumpier as opposed to when carving. This is based on the physical interaction between the snowboard and the snow, caused by the angle with which the snowboard is cutting in the snow. Our algorithm takes advantage of this property by analyzing the gyroscope data of the yaw axis. A peak detection as shown in Algorithm 1 with a very small δ and no groundband b recognizes the bumping of the board along its yaw axis. The number of detected peaks between two turns is divided by the time between these turns. If this ratio exceeds the carving-versus-skidding threshold cvs, the technique between the two turns is considered to be skidding, and carving otherwise. The algorithm is formalized in Algorithm 3. An example can be found in Figure 11.

6 Evaluation in Real-Life Experiments

The functionality of the activity recognition component of our system was evaluated on five different ski slopes in the Swiss ski resorts Braunwald, Savognin and Grindelwald.

Algorithm 3 detectTechniques($turns, y, \delta, b, cvs$)

Require: y gyro data of yaw axis
Require: cvs carving-versus-skidding threshold
$[maxpeaks, minpeaks] =$ detectPeaks(y, δ, b)
for all $t_i \in turns[1 : end - 1]$ **do**
    $n_i =$ number of peaks in y between t_i and t_{i+1}
    $\tau_i =$ time between t_i and t_{i+1}
    if $n_i / \tau_i > cvs$ **then**
        add "skidding" to *techniques*
    else
        add "carving" to *techniques*
    end if
end for
return *techniques*

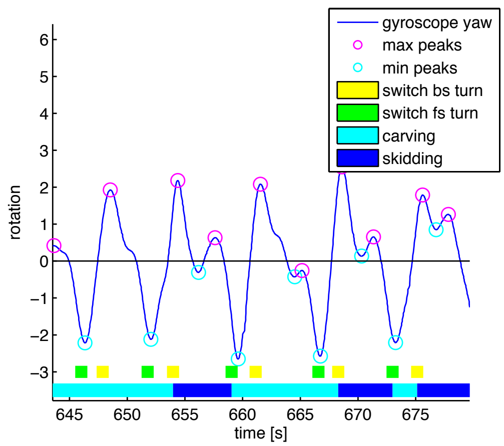


Figure 11. Technique detection. Several peaks between two consecutive turns are an indication for a bumpy flight of the snowboard and thus skidding

6.1 Experiments

We recorded over thirty descents of seven snowboarders, six advanced riders and one professional snowboarding teacher. Having been equipped with the wearable sensor system, the test subjects were instructed to perform all the different activities and state transitions of our snowboarding from Figure 5 on the ski slope. Additionally, the rides were recorded with a video camera by an experienced skier, who safely followed the descending test subjects. To synchronize the sensor data stream with the video frames, the test subjects jumped into the air at the beginning and the end of the ride. The sensor data streams were later labeled manually according to the snowboarding model with the help of the video ground truth. Despite the harsh conditions on the slope, the Bluetooth connection between the Eee PC and the Board IMU was never dropped and no data were lost.

Performane of Activity Recognition: To assess the performance of the activity recognition algorithms, we performed a leave-one-person-out cross-validation. That is, the performance of the detection algorithms was evaluated for each test subject, after their parameters such as δ, b, and cvs were optimized for all the other subjects. The achieved results are thus independent of user, snowboard, slope and snow characteristics. The accuracies of the activity recognition algorithms are summarized in Figure 12, whereas Figure 13 shows the performance of the turn detection algorithm.

Detection	Accuracy
Action (GPS)	90.5 %
Action (IMU)	88.2 %
Edge	78.8 %
Direction	91.3 %
Technique	89.5 %

Figure 12. Accuracy of activity recognition algorithms. Each sample of the sensor data was classified separately by the detection algorithms. The accuracies refer to the fraction of the samples that were classified correctly with respect to action, direction, edge and technique

Turns	Count	Ratio
Performed	440	100 %
Correctly detected	398	90.5 %
Correctly classified	390	88.6 %
Deletions	42	9.5 %
Insertions	49	11.1 %

Figure 13. Performance of turn detection algorithm

Action Detection: The action detection algorithm based on GPS (90.5 %) slightly outperforms the one taking the gyroscope data of Board IMU (88.2 %). The reason for this is that a rider can move his snowboard even while sitting on the ground. This evaluation shows that both approaches are feasible. A combination of the two may even yield better results.

Turn Detection: For the analysis of the performance of our turn detection algorithm, we use the following criteria. An occurred turn is considered to be *detected correctly* if and only if the time difference between the real and the detected turn is less than a given threshold Δt. A correctly detected turn is referred to as *correctly classified* if its direction and edge have been identified correctly. A *deletion*, also known as a false negative, is a turn that has not been detected. An *insertion*, also referred to as a false positive, is a detected turn with no corresponding occurred turn within a time span of Δt units. An illustration of these definitions is shown in Figure 14. The results of the performance analysis are summarized in Figure 13. We chose $\Delta t = 0.5\,\mathrm{s}$ as it is unfeasible for snowboarders to perform two turns within this time span. 90.5 % of the 440 performed turns were *detected* correctly, whereas 88.6 % of all turns were also *classified* correctly, that is, edge and direction were determined right. 9.5 % of the turns were missed, whereas 11.1 % were false positives.

Edge, Direction and Technique Detection: The edge, direction and technique snowboarders use can be determined

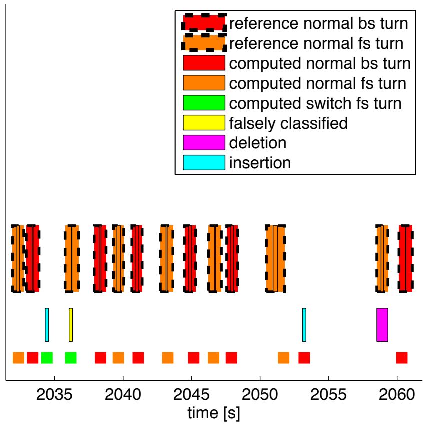


Figure 14. Turn detection errors. The third computed turn does not have a corresponding occurred turn and is thus a false positive (insertion). The fourth turn was detected correctly. However, it was classified as a switch frontside turn rather than a normal frontside turn. The penultimate reference turn was not detected at all (deletion)

with accuracies of 78.8 %, 91.3 % and 89.5 % respectively. These figures refer to the fraction of the samples that were classified correctly regarding edge, direction and technique.

7 Conclusion

Traditional approaches for activity recognition in the snowboarding domain are based on insoles measuring the pressure distribution inside the boots. Previous studies have revealed that although insole-based systems can detect turns with an accuracy of up to 98 % under certain conditions, they entail several disadvantages. Extra pairs of insoles in the boots are uncomfortable to wear, require long setup times due to user-specific calibrations and cannot be adjusted to different shoe sizes. Moreover, they are especially error-prone in environments with low temperatures. We have therefore developed a simple alternative sensor system based on a mobile computing device with a GPS receiver, and a gyroscope attached to the center of the snowboard, which is capable of recognizing turns and distinguishing nine different snowboarding activities. It is easy to set up as the gyroscope can simply be taped onto the snowboard without any user-specific calibrations. Experiments with seven snowboarders on five outdoor ski slopes showed that our sensor system is capable of withstanding harsh conditions such as temperatures as low as −25 °C, and, despite being a first prototype, can recognize turns with an only slightly less accuracy of 90.5 %. However, the recognition works independently of user, snowboard, slope and snow characteristics. In addition to the mere detection of turns, our system can recognize whether the snowboarder is riding on the frontside or the backside of the board (edge), whether she is going forwards or backwards (direction) and reveals whether she is carving or skidding (technique) with similar accuracies.

8 Outlook

Boosted by these promising results, we are striving to implement our vision of an interactive snowboarding teacher. One step towards it is the improvement of the presented activity recognition system. Currently, the Board IMU is taped onto the snowboard, which makes it an easy target for being dropped during rides in ski lifts. To make the sensor system yet more robust and unobtrusive, the Board IMU will be integrated into the bindings of the snowboard. Moreover, a mobile phone based solution is currently under development. As previous studies have shown [6], pressure insoles reveal interesting riding statistics, but entail several drawbacks. Therefore, we are currently working on the development of pressure sensing units, which can be integrated into snowboarding socks and the bindings of snowboards. First studies suggest that gyroscope-based activity recognition can also be applied to snowboarding-like sports such as skiing, skateboarding, surfing and wakeboarding. We will thus further explore the functionality of our algorithms in these domains.

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