

A multi-sensor system for automatic analysis of classical cross-country skiing techniques

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Published online: 12 October 2017
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Abstract Commercial systems utilizing data from inertial measurement units (IMUs) to analyse movement patterns have not yet been adapted to monitor daily training in cross-country (XC) skiing. The main purposes of this study are to investigate: (1) the feasibility and potential of a multi-sensor system consisting of a heart rate sensor, global navigation satellite systems (GNSSs) data and seven IMUs placed at multiple locations on the body for outdoor XC skiing, and (2) the validity of employing hard decision rules based on the correlation between arms and legs for detecting sub-techniques in classical XC skiing. All sensor data were synchronously sampled and synchronized with GNSS data from a commercially available sports watch while XC skiing on varying tracks, from amateur skiers and world-class athletes. An algorithm based on the correlation of the angular velocity of arms and legs was developed to detect the three main classic sub-techniques, diagonal, double poling with a kick and double poling. Other sub-techniques were classified as miscellaneous (0–20%). The system is shown to work well outdoors on snow during different conditions, and the implemented algorithm was validated by video analyses to detect the three sub-techniques with a sensitivity of 99–100%. This study is the first to detect and link sub-techniques in XC skiing to GNSS data, thereby associating the detection and distribution of sub-techniques to different terrains. Such information gives

insight into the technical and tactical aspects of skiers' daily training and competitions, thereby providing a tool for coaches and athletes.

Keywords Cross-country technique · Classical sub-techniques · Inertial measurement units · Physiological sensors · Movement sensors

1 Introduction

Cross-country (XC) skiing is a demanding outdoor endurance sport, involving whole body exercise while skiing across varying terrain. Within the classic and skating techniques, XC skiers continuously shift between various sub-techniques according to the track topography used in training and competitions [1]. In the classical technique, the main sub-techniques are diagonal stride (DIA), double poling with a kick (DK) and double poling (DP) [2]. In addition, the herringbone technique [3], where the skis are angled and edged to increase static friction, is used in steep uphill terrain, the tuck position in downhill and various turn techniques are employed at narrow turns [4].

The DIA technique is primarily used on moderate to steep uphill slopes, where a high ratio of propulsive to recovery phase provides advantages. DIA follows a diagonal coordinated pattern as known from walking and running, where arms and legs move contralaterally and produce propulsive force simultaneously [5, 6]. In contrast, DP is most frequently used on relatively flat terrain, although recently also on steeper uphill by elite male skiers. A symmetrical and synchronous movement of both arms, where all propulsive forces are exerted through the poles, characterizes DP [7]. The arm motion in DP is supported by considerable trunk flexion in the poling phase

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before the lower limbs elevate the centre of mass by extending the ankle and knee joints in the repositioning phase [8]. DK is commonly used in the transitions between DIA and DP, and it has an upper body movement relatively similar to the movement in DP, supported by propulsion from either a left or right leg kick in between the DP actions [9].

To characterize and quantify such sub-techniques and their kinematic patterns in the field, microsensor technology has shown potential to measure this in real time without requiring the use of resource-intensive methods such as video analysis. One of the first attempts, by Marsland et al. [10] visually identified cyclical movement patterns in the sensor data from one inertial measurement unit (IMU) mounted on the skier's back in both skating and classical sub-techniques. In a follow-up study, the same group was able to automatically classify sub-techniques and kinematics in classic with a limited precision using a seven-step algorithm [11]. Furthermore, Markov chain of multivariate Gaussian distributions has been used to classify sub-techniques in skating using data from a mobile phone [12], as well as an automated identification system has been developed based on correlation classified sub-techniques using sensors placed on hands and skis [13, 14].

To date in XC skiing, microsensor units have not yet been synchronized with global navigation satellite system (GNSS) data, although the detection of sub-techniques and kinematics is clearly influenced by speed and incline. Sakurai et al. [13] used a small GNSS device to record the current inclination and speed of an athlete when detecting the classical-style sub-techniques, but their study was performed using roller skis and they did not link the sub-technique distribution to the terrain. In addition, the potential of using many time-synchronized IMUs, distributed on several places on the upper body, arms and legs at the same time, has not been examined. Therefore, the main purposes of this study are to investigate: (1) the feasibility and potential of a multi-sensor system consisting of a heart rate sensor, GNSS and seven IMUs placed at multiple locations on the body for outdoor XC skiing, and (2) the validity of employing decision rules based on the correlation between the angular velocity on arms and legs for detecting sub-techniques and cyclic patterns in classical XC skiing.

2 Methods

2.1 Description of sensor system

The prototype multisensory system consists of two types of sensor modules described in previous publications, one unit of IsenseU-HR+ [15] and six units of IsenseU-Move+ [16] connected to a small computer (Odroid-U3) that controls,

synchronizes and logs sensor data. The IsenseU-HR+ [weight 35 g (75 g including belt), size 7.7×4.6 cm] calculates the heart rate based on ECG data (250 Hz), skin temperature on the chest (every third second), in addition to triaxial accelerometer and gyroscope data (20 Hz), and transmits data wirelessly using Bluetooth 2.1. To measure the heart rate and skin temperature, the sensor must be placed on the skin of the chest using a textile electrode belt. IsenseU-Move+ (weight 17 g, size 5.3×3.7 cm) has a triaxial IMU, consisting of a triaxial accelerometer, gyroscope and magnetometer in addition to several other sensors that are not used in this study, and it transmits data wirelessly using Bluetooth Smart. This study focuses mainly on movement data and for each time stamp there are a total of 60 channels related to motion, 9 channels from each of the six IsenseU-Move+ units and 6 channels from the IsenseU-HR+ unit; see Table 1. The sampling frequency of the movement data was 20 Hz, and all channels were synchronized in time to an accuracy of at least 30 ms, with the detailed procedure for solving this explained in detail previously [17].

During the testing, the IMUs were placed on the following locations using straps with velcro: upper back, lower back, left and right arm, and left and right ankle; see Fig. 1. The Odroid with battery (weight 370 g) was carried by the test participants in a small backpack. The multi-sensory system was controlled by employing a custom-made Web page accessed by an internal Wi-Fi set up by the Odroid. The Web page made it possible for the operator to check the status, select sensors and start and stop both the system and logging. The Garmin Forerunner 920XT (Garmin Ltd., Olathe, KS), with both GPS/GLONASS and a barometric altitude monitor, was included in the system and used to measure the position and altitude with a sampling frequency of 1 Hz (the highest frequency available). In this study, the GNSS was mainly used for comparing the identified techniques throughout the track. Hence, a frequency of 1 Hz was sufficient for segment definitions and



Fig. 1 Location of the seven triaxial IsenseU-Ski sensors and sensor orientation relative to the skier

coarse speed estimates, under the assumptions that the segments were sufficiently long and that the athlete did not change speed too rapidly (fall or crash preventive manoeuvres) at the points of segment definition. Since the position data from the watch and the data logged on the Odroid have time stamps, they were synchronized obtaining both the position and the sensor data from the skier. A standalone graphical user interface (GUI) was implemented in MATLAB (The MathWorks, Inc., MA, USA) and used to interpret and analyse data from the sensor system immediately after the training sessions. In the custom-made GUI, the results from the sessions were displayed as detailed position tracks in a map in addition to graphs with altitude, speed (change in position per time unit), heart rate and arm frequency as a function of distance, all with the coinciding sub-techniques given in colours. Additional functionality included quantifying parameters for selected segments. For example, if a skier had run a specific track twice during a session, it was easy to compare the effort (time, heart rate, speed, etc.) of the different runs; see Table 5.

2.2 Measurements

2.2.1 Participants

Datasets were recorded from 11 different participants, 10 males and 1 female [(mean \pm SD) of age 30 ± 7.6 years (range 16–43), body height 180 ± 6 cm, body mass 73.0 ± 8.4 kg], with levels of skill ranging from amateur to World Cup skiers; see Table 2. Participants with different performance levels were chosen to examine whether the system could classify sub-techniques and analyse the performance for both amateur and professional skiers. All protocols and procedures were explained verbally to each skier and written informed consent was obtained. The Norwegian Centre for Research Data (NSD), Norway, approved the study (ID 49865 Analyse av teknikkdistribusjon og temporale mønster i langrenn).

2.2.2 Overall design

Data were collected in different types of tracks and snow conditions (Table 2) to investigate the feasibility and potential of the system independent of the terrain. The ground truth of the datasets was obtained from video and used to validate the classification algorithm. The video was captured with Garmin VIRB (Garmin Ltd., Olathe, KS) placed on the forehead of a skier following the test participant. The datasets manually synchronized to the video were automatically divided into cycles to ease the manual labelling of sub-techniques. The cycles were automatically segmented using Gaussian low pass-filtered data from one axis of the gyroscope on the left arm. Start/stop of a cycle was defined at the time the arm was extended behind the participant. All 11 skiers were test participants in one or more of the field tests, and each session lasted between 15 and 60 min. The thermal environment varied from very cold (-18 °C) to very hot ($+10$ °C). The tracks also changed across the different test days, from being solid with high friction via icy tracks with low friction, to warm weather with wet snow and high friction. The protocol was slightly different for each field test due to differences in the daily conditions, environment and tracks. However, all tests involved all sub-techniques and the skiers were instructed to ski at both moderate intensity (75–87% of maximum heart rate) and high intensity (87–97% of maximum heart rate) based on their own perception of intensity.

2.3 Post-treatment and calibration of raw data

The different data channels were continuously synchronized in time (< 30 ms) [17] before the time-synchronized raw data were post-processed using MATLAB. Due to different sampling rates, the data streams needed decimation and interpolation to get a structured dataset sorted by a time stamp with a corresponding sample for each data channel (target 20 Hz). Data loss was tagged accordingly,

Table 1 Overview of the location of the sensors

	Chest	Upper back	Left arm	Right arm	Low back	Upper back	Left leg	Right leg
3D accelerometer (20 Hz)	X	X	X	X	X	X	X	X
3D gyroscope (20 Hz)	X	X	X	X	X	X	X	X
3D magnetometer (20 Hz)		X	X	X	X	X	X	X
Skin temperature (0.3 Hz)	X	X						
Heart rate (every heart beat)	X							
GPS/GLONASS (1 Hz)			X					
Barometric height (1 Hz)			X					

Table 2 Overview of performance level, different types of test terrain, track condition and period of data collection for 11 cross-country (XC) skiers

Parameters	Test location			
	Competition course Holmenkollen	Competition course Natrudstilen	Flat terrain Sjusjøen	Mountain terrain Sognefjellet
Participant 1 ^a				
Air temperature	0 °C	+ 8 °C		+ 8 °C
Snow condition	Wet and soft	Wet and soft		Wet and soft
Racing time	00:15:50	00:37:15		00:27:42
Participant 2 ^a				
Air temperature				+ 8 °C
Snow condition				Wet and soft
Racing time				00:51:26
Participant 3 ^b				
Air temperature		+ 5 °C		
Snow condition		Icy		
Racing time		00:23:11		
Participant 4 ^a				
Air temperature	0 °C	+ 5 °C	– 18 °C	+ 8 °C
Snow condition	Wet and soft	Icy	Hard-packed	Wet and soft
Racing time	01:06:26	00:38:17	00:37:50	00:32:14
Participant 5 ^b				
Air temperature				+ 8 °C
Snow condition				Wet and soft
Racing time				00:25:27
Participant 6 ^b				
Air temperature				+ 8 °C
Snow condition				Wet and soft
Racing time				01:03:03
Participant 7 ^b				
Air temperature		+ 5 °C		
Snow condition		Wet and soft		
Racing time		00:20:41		
Participant 8 ^a				
Air temperature			– 18 °C	
Snow condition			Hard-packed	
Racing time			00:32:16	
Participant 9 ^a				
Air temperature		+ 8 °C		
Snow condition		Wet and soft		
Racing time		00:56:08		
Participant 10 ^b				
Air temperature		+ 5 °C		
Snow condition		Icy		
Racing time		00:21:43		
Participant 11 ^a				
Air temperature		– 10 °C		
Snow condition		Hard-packed, icy		
Racing time		00:24:46		

^aAmateur skier

^bProfessional skier

thereby enabling downstream algorithms to track the data's validity. Data loss was due to limitations in the wireless technology; the human body is an excellent shield for wireless signals and interruptions may occur when the sensors are located close to the body. This is worse outdoors than indoors due to less reflection from obstacles. During these tests, the problem was partially solved by automatically forcing a reconnect after interruptions in the wireless link; however, an internal memory with temporary storage of data during interruptions should be added to the sensors to completely solve this issue.

As the sensor modules were fixed to the participant's body, both the sensor unit positioning and orientation will vary from session to session. To normalize the data, a calibration routine was necessary. The goal of the calibration process was to compute the axis that would capture the most angular motion (in terms of variance). This axis was assumed to be perpendicular to the sagittal plane (see Fig. 1), also referred to as the lateral axis, and the sensor data were rotated according to this reference. The calibration process required datasets satisfying certain constraints (i.e., the athlete initially needed to follow a simple protocol). The constraints were typically satisfied if the participants performed large movements of arms, legs, chest and back along the initial part of the track on a flat terrain (typically obtained from clean DIA or DK techniques).

2.4 Classification of sub-techniques

2.4.1 Classical sub-technique identification from IMUs on arms and legs based on correlation heuristics

In this work, the main classical sub-techniques (DIA, DK and DP) used by a skier while following the skiing track have been classified. The method was based on data from four of the IMUs, placed on the athlete's extremities (arms and ankles). The information from the angular velocity channels of these sensors were thus highly related to the main mechanisms of the kinematics of the skier and are therefore intuitive and closely related to the visual characteristics of the techniques. All movement patterns not satisfying the criteria for DIA, DK and DP were grouped as miscellaneous (MISC). This included the herringbone technique, undefined technique combinations, technique transitions, turn techniques and downhill postures.

The classification was based on three assumptions:

(1) A synchronized dataset of at least one full technique cycle was available and parameterized by the recorded data within a time window of size ws . That means that for a given technique evaluation time point t_i , the athlete had completed at least one full cycle of a given technique within the time interval $[t_i - ws/2,$

$t_i + ws/2]$. Remark: we have implemented a fixed ws for the whole dataset, and there is therefore a trade-off between identifiability and uniqueness. If ws was too small, the window may not contain sufficient information and if ws was too large, the window may contain cycles of different sub-techniques.

(2) The data from both arms and legs were sufficient for reconstructing a movement cycle. This means that the data loss from each sensor must be less than $(1 - a)ws$, where a is a parameter dependent on grouping criteria and features. Remark: the parameterization of this assumption was conservative as it does not distinguish between "bulk" data loss or data loss distributed evenly over the window. For example, a 50% data loss can be tolerable if it was due to reduced sampling rate, while it would render the identification of DK unidentifiable if a continuous batch of data from the kicking leg was missing.

(3) The body-attached sensors were calibrated so that the angular rate around the sagittal perpendicular axis was sufficiently estimated, also when dependent on grouping criteria and features.

The phase shift of the arm sensors data was used as a feature for classifying DP and DIA. By calculating the correlation between the arms angular velocity measures along the axis perpendicular to the athlete's sagittal plane, the in-phase and anti-phase (180° phase shift) motions of DP and DIA were captured. The relative angle between the leg sensors was used to distinguish between DP and DK. This was done by calculating the difference in angular velocity measures from the two foot sensors along the axis perpendicular to the athlete's sagittal plane. This angular velocity difference was further used to estimate the relative angle between the two legs so that the DP and DK techniques could be separated. Combined, the arm and leg work gave a simple set of rules where DIA and DP/DK were separated by the arm work, and DP and DK were further separated by the leg work.

In Fig. 2, the classification algorithm is illustrated using an example from a professional skier (participant 3) at Natrudstilen. The upper graph displays the angular velocity of the two arms; during DIA the arms had opposite movements, while during DK and DP the arm movements were synchronized. The graph below displays the relative angle between the leg sensors, showing that the relative angles between the legs were high for every 'diagonal kick' for DIA and that there was an opposite spike in the relative angle for every kick for DK, while the difference was irregular and relative small for DP. In addition, the figure displays the arm frequency, as well as arm correlation, leg work features and clustering for each of the different sub-techniques. The arm frequency was calculated by computing the autocorrelation of the signal channel

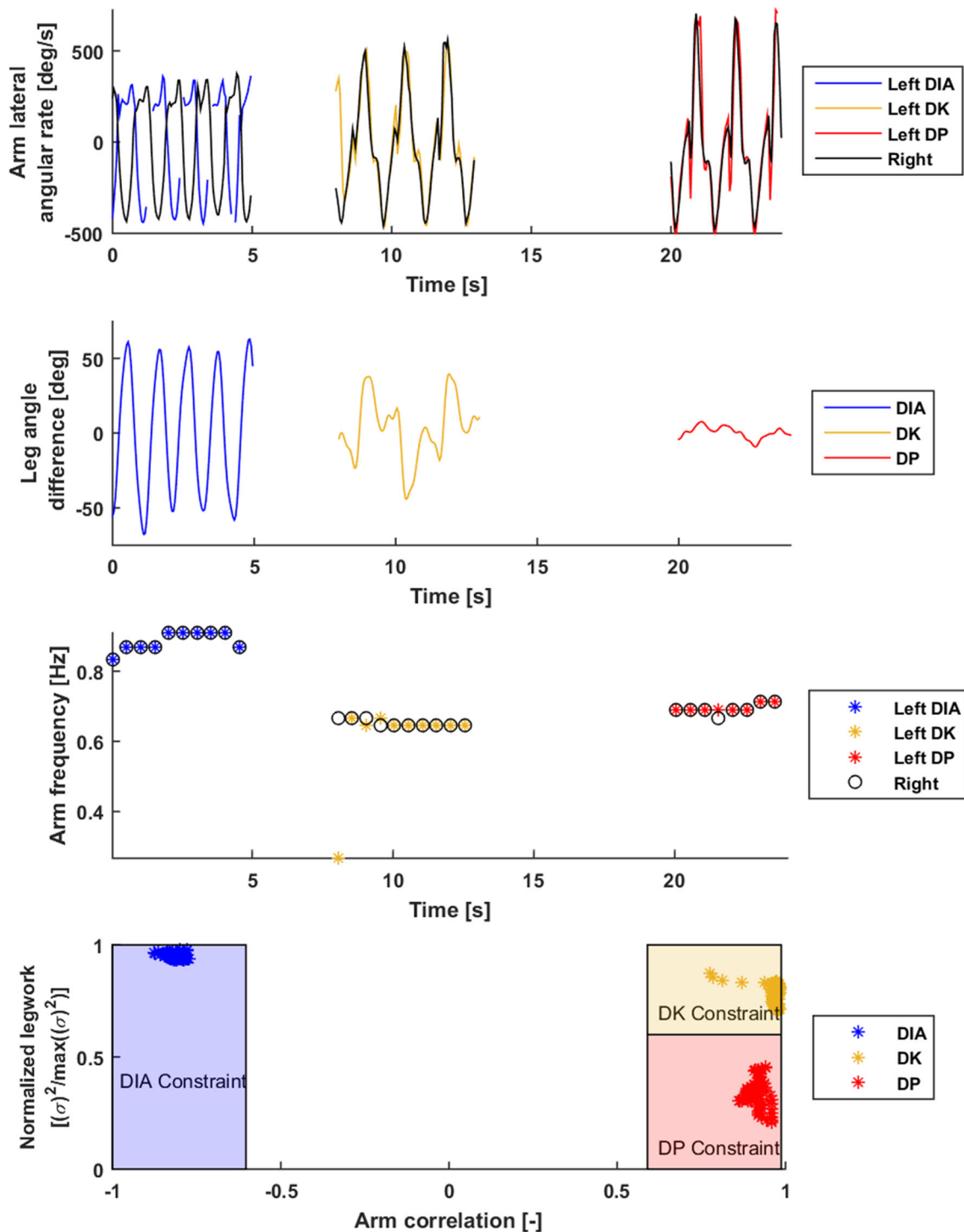


Fig. 2 Classification of sub-techniques [diagonal (DIA), double poling with a kick (DK) and double poling (DP)] for a professional skier (participant 3 at Natrudstilen); the two upper rows present the input data to the algorithm for the arm and leg activity for each sub-

perpendicular to the sagittal plane and using the peak with the highest prominence (topography) to define the signal delay. The inverse of this delay was used as the cycle frequency estimate.

technique, the third row shows the arm frequency estimates in relation to classification, while the lower row displays the output data in the form of classification as a function of arm correlation and legwork

2.4.2 Pseudocode of the classification algorithm

The pseudocode of the classification algorithm is given below. For each new sample of data, the window was

updated by removing the oldest sample and the following calculations were made:

Arm work:

The total variance of the arms V_{TA} were calculated and used to check if the arms were moving significantly.

$$V_{Al} + V_{Ar} = V_{TA} > T_{AV}.$$

Here, V_{Al} and V_{Ar} are the variance of the left and right arm, and T_{AV} is the tolerance of V_{TA} . We then calculate the correlation C_A between the arm angular velocity measures along the axis perpendicular to the athlete's sagittal plane as follows:

(a) If $C_A > T_{DP}$, then the athlete uses DP or DK.

(b) If $C_A < T_{DIA}$, then the athlete uses DIA.

Here, T_{DP} and T_{DIA} are the tolerance of DP and DIA.

Leg work:

The difference in angular velocity was calculated from the two foot sensors along the axis perpendicular to the athlete's sagittal plane. We calculated the variance V_{La} of this difference as follows:

(a) If $V_{La} > T_L$, then the athlete uses the leg.

(b) Otherwise, the athletes do not use the leg.

Technique decision:

This gives the following technique grouping:

If $V_{TA} > T_{AV}$ and the assumptions (described earlier) holds:

(a) DP: if $(C_A > T_{DP})$ and $(V_{La}) \leq T_L$,

(b) DK: if $(C_A > T_{DP})$ and $(V_{La}) > T_L$,

(c) DIA: if $(C_A < T_{DIA})$,

(d) MISC: if not (DP|DK|DIA).

The limits for the constants in the pseudocode (T_{AV} , T_{DP} , T_{DIA} , T_L) were manually set, to group decisions for as much of the dataset as possible without being influenced by false identification due to insufficient information.

2.4.3 Validation of sub-technique classification

To evaluate the performance of the sub-technique classification, selected datasets were manually combined and synchronized with a video of the skier into a final video showing the skier and selected data channels from IsenseU-Ski. Using this video, each cycle was manually labelled as DP, DK, DIA or MISC. Manual classification of video is time consuming; therefore, only parts of the measured data were used for validation. In some of the earlier sessions, video was not used; and in some of the sessions, there was a high rate of dropouts from one or more sensors. The selection of datasets used for validation was therefore based on the requirement that the dataset was as complete as possible and there was video evidence. In total, datasets were classified from six participants while skiing with moderate intensity using their preferred sub-technique

according to the terrain. Technique cycles missing more than 20% of the sensor data were deemed invalid and ignored in the validation. The data loss limit was included to prevent the algorithms from classifying the cycles based on insufficient/uncertain information. For example, missing leg movement information during the kick phase of the DK would have incorrectly made the algorithm classify the technique as DP. Out of the six participants, three were amateurs and three were professionals, five were male and one was female. The datasets were acquired at Natrudstilen and Sognefjellet. The statistical analysis on the validation of sub-technique classification was done using confusion matrices. In the confusion matrices presented, the columns represent the manually labelled class and the rows represent the class classified by the algorithm. Ideally, all cycles should end up on the diagonal, which means that they are classified to the correct class. However, if a cycle appears, e.g., in the second lowest square to the left it means that the cycle was labelled as DP, but wrongly classified as MISC. The sensitivity (true positive/(true positive + false negative)) is shown in the lower row, and the precision (true positive/(true positive + false positive)) is shown in the column to the right. The mean sensitivity and precision for DIA, DK and DP are reported in Table 4 for each dataset, along with the dataset's duration, number of cycles and the balance of each detected technique measured in the number of cycles.

3 Results

This section is divided into three sub-sections. The first sub-section demonstrates the potential of the available data from the sensor system and illustrates the possibilities for further developments. In the second section, the validation of the sub-technique characterization is provided. Finally, the last sub-section exemplifies how sub-technique characterization can be useful by comparing the performance data of two different skiers.

3.1 Sensor system output and potential for analysis of skiing technique quality

Over a period of 5 months, 9 h and 34 min of data was measured. Although a structured study of user friendliness has not been done, the test participants were asked to rate how comfortable the system was to wear during the session. All participants responded that the backpack was comfortable to wear and they did not notice the sensors or backpack after it had been mounted. One participant made the remark that the left IsenseU-Move arm sensor was somewhat in conflict with the watch.

Fig. 3 Calibrated gyroscope data at six different positions (left/right arm and leg, upper and lower back) of an amateur skier (participant 4) during diagonal (DIA), double poling with a kick (DK) and double poling (DP) in flat terrain. The colours represent the neighbouring cycles shifted in time to show the cyclic repetitive movement patterns

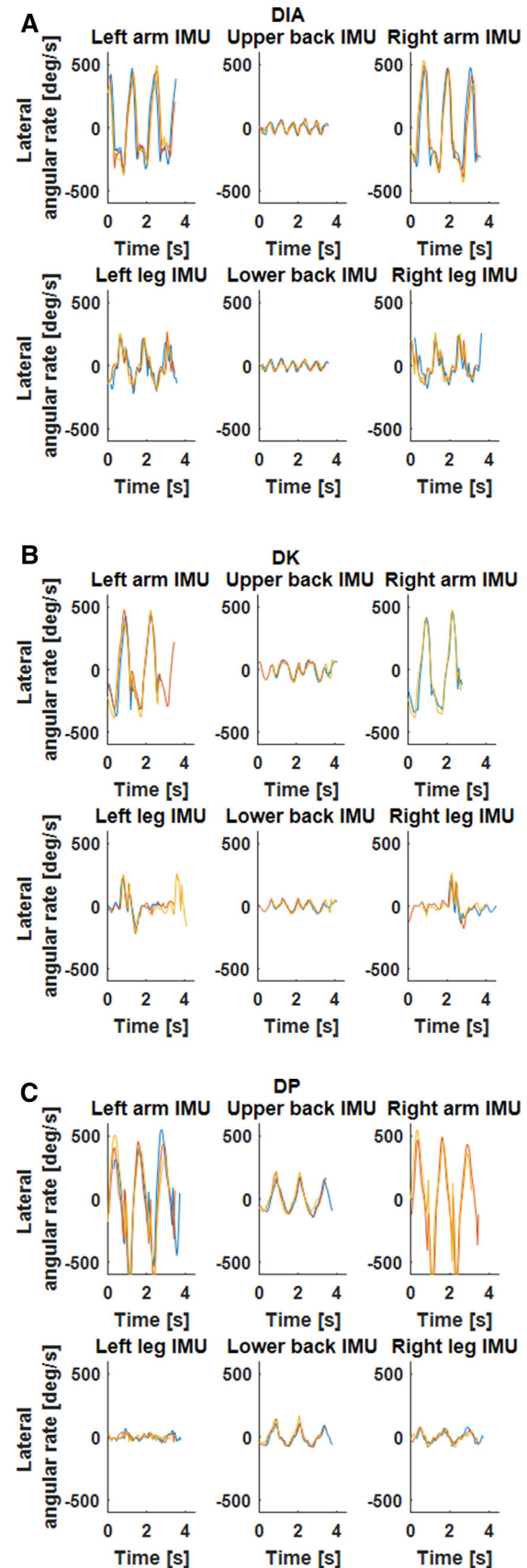
3.1.1 Cyclic relations on different body parts

This sub-section illustrates how features related to kinematics and timing of body segments may be extracted from the raw data and used in technique training by athletes and coaches.

Four cycles of pre-processed and calibrated gyroscope data from six different parts of the body of an amateur skier (participant 4) while skiing DIA, DK and DP are displayed in Fig. 3. The figure shows that the multi-sensor system was able to measure a repeatable cyclic pattern for each body part for all three sub-techniques in amplitude, frequency and shape. This repeatability could be used as a feature for evaluating the skier's performance over time, for example to evaluate if the skier was able to maintain the same cycles when he is fatigued at the end of an interval session or a race. Potentially, this could also be done in real time, since the system can recognize when the quality of the technique drops and notify the skier so that he/she can compensate for this in the rest of the workout/competition. In addition, the figure shows that each sub-technique has its own characteristic patterns that can be used to classify sub-techniques by combining different sensors and also to analyse how the skier can improve the specific sub-technique. For this amateur skier, the movements of the upper body were much more pronounced during DP than during DIA and DK. This is as expected for DIA, but not for DK.

3.1.2 Difference in timing between different body parts

Body part timing will provide important insight into tracking the athlete kinematics, and previous papers show that the timing of different body parts may relate to effective force production during a movement cycle and explain why different techniques are more or less efficient at a given condition [5–7, 18]. The phase differences between the movements of the different body parts can be calculated by selecting a reference channel and correlating a data 'window' from each of the other channels with the reference. Figure 4 shows examples where the phase differences have been removed for an amateur skier (participant 4) during DIA, DK and DP based on the lateral axis data from the gyroscope sensor for arms, legs and torso. Here, the sensors on the right arm and right leg were chosen as the respective refer-



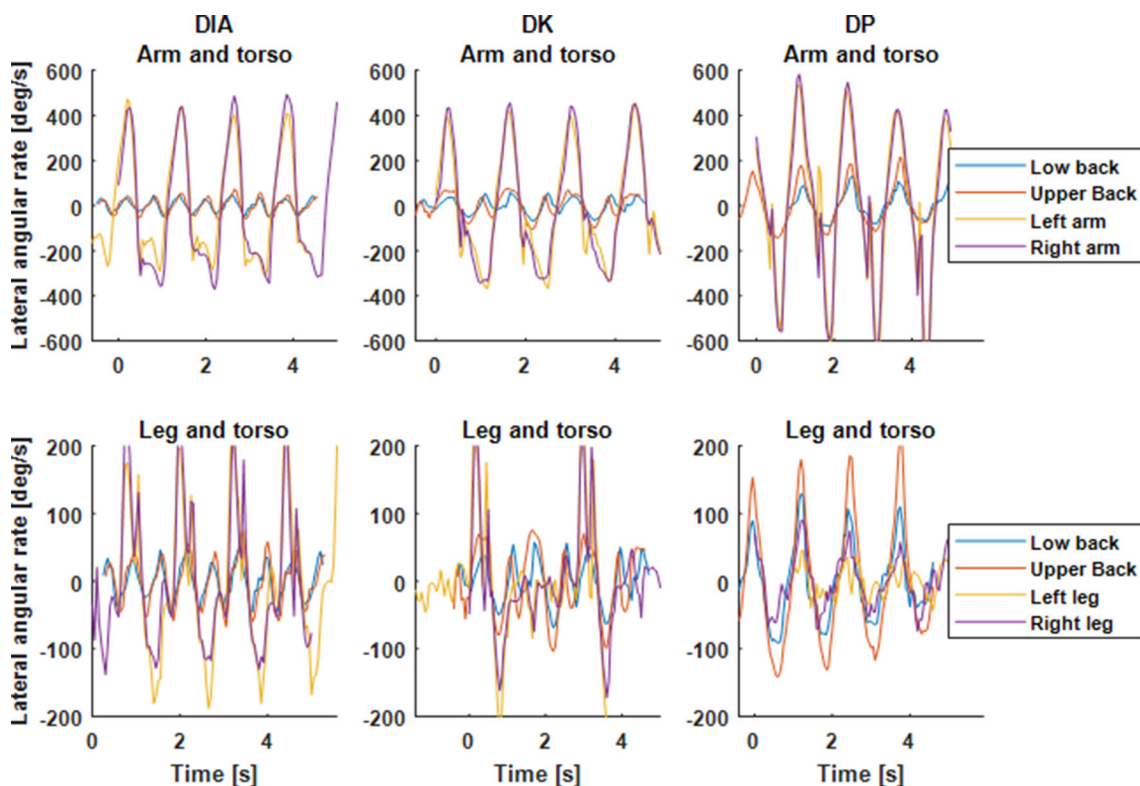


Fig. 4 The signals' correlations following removed phase differences between arms and torso relative to the right arm (upper graphs), and for leg and torso relative to the right leg (lower graphs) for an amateur skier (participant 4) while skiing diagonal (DIA), double poling kick (DK) and double poling (DP) techniques

Table 3 Phase differences (s) between arms and torso [relative to right arm (in italic)] and leg and torso [relative to right leg (in italic)] for an amateur skier (participant 4) while skiing with diagonal (DIA), double poling kick (DK) and double poling (DP) techniques

Timing (s)	Low back	Upper back	Left arm	Right arm	Low back	Upper back	Left leg	Right leg
DIA	-0.5	-0.45	-0.6	<i>0</i>	0.25	0.3	0.6	<i>0</i>
DK	-0.35	-0.45	0	<i>0</i>	-0.3	-0.4	-1.4	<i>0</i>
DP	0.85	-0.45	0	<i>0</i>	-0.4	-0.4	0.9	<i>0</i>

The body movement synchronization precision is limited by the system data sampling resolution at 50 ms and sensor time-synchronization precision > 30 ms

ences. The phase shifts were found by the maximal correlation between the reference and the other channels, and the figure shows the selected window of data plotted after the phase shifts have been compensated for. The phase differences shown in the plot are quantified in Table 3. The relative motion between the upper and the lower part of the back were shifted by 0.05 s for DIA and -0.1 s for DK compared to the leg motion. As expected, arm motions were synchronized for DK and DP and asynchronous for DIA. Leg motions were as expected for DP and DK, but during DP there were limited and noisy movements. Phase differences, like in the example showed here, are believed to be essential in the qualitative evaluation of ski technique.

3.2 Validation of sub-technique classification

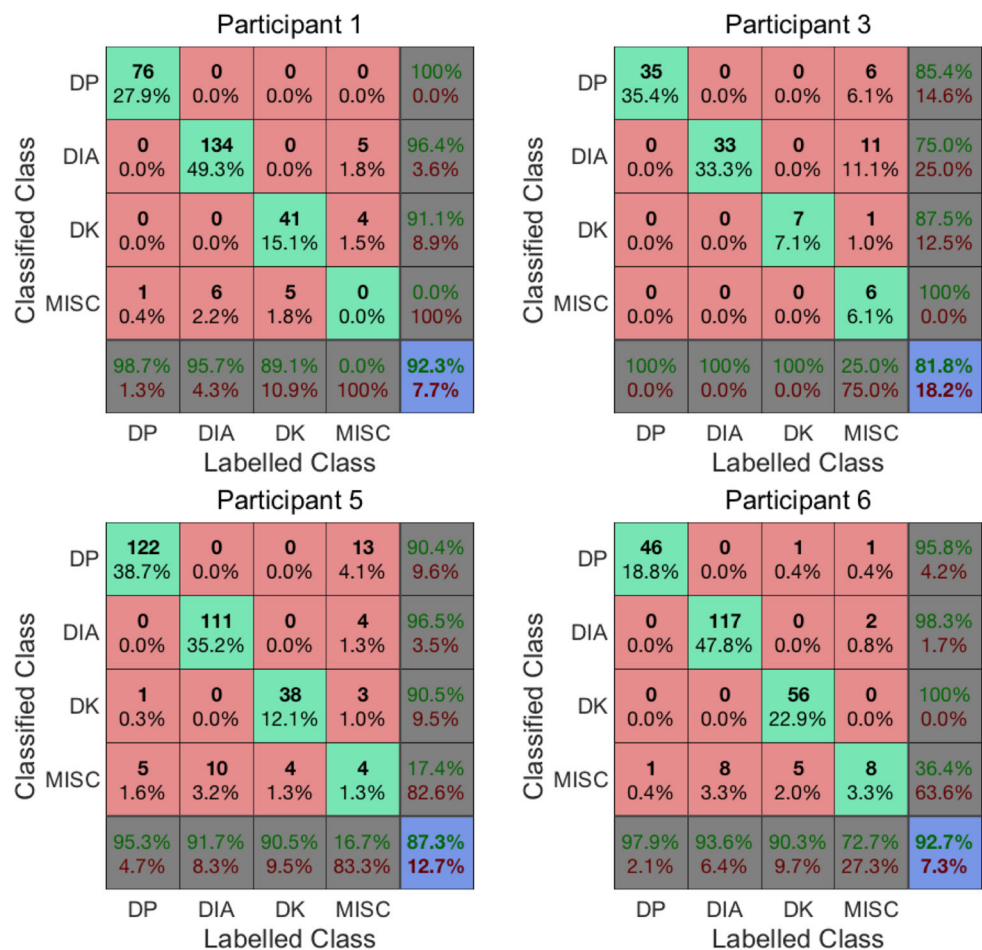
In this sub-section, the results from the validation of the classification of sub-techniques are presented. The results are presented for all participants in Table 4, and as confusion matrices for four of the participants, two with the highest and the two with the lowest sensitivity/precision in Fig. 5. The sensitivity and precision reported in Table 4 were based on the classification of DP, DIA and DK; the cycles classified or labelled as MISC were left out, as the algorithm does not implement rules for distinguishing other sub-techniques. The MISC classification/values are however included in the confusion matrices in Fig. 5, and the rightmost columns show the potential for increasing the

Table 4 Datasets used for validation of sub-technique classification with duration of time, number of cycles, the balance of the detected techniques and the sensitivity and precision for the classification of diagonal (DIA), double poling with a kick (DK) and double poling (DP)

Parameters	Participant 1 Sognefjellet	Participant 2 Sognefjellet	Participant 3 Natrudstilen	Participant 4 Sognefjellet	Participant 5 Sognefjellet	Participant 6 Sognefjellet
Racing time	11:53	14:22	04:04	14:44	14:30	14:37
# Cycles	272	226	99	396	315	245
DIA (% Cyc)	52	29	33	42	38	51
DK (% Cyc)	17	13	8	10	13	25
DP (% Cyc)	28	53	35	41	41	19
MISC (% Cyc)	3	5	24	7	8	5
Sensitivity (%)	100	100	100	100	99	99
Precision (%)	100	100	100	99	99	99

MISC other techniques than DIA, DK and DP, *Sensitivity* average true positive rate (true positive/(true positive + false negative)) for DIA, DK and DP, *Precision* average positive prediction rate (true positive/(true positive + false positive)) for DIA, DK and DP, % Cyc percentage in relation to the total number of cycles

Fig. 5 Confusion matrices for four participants while skiing with medium intensity in classical sub-techniques: diagonal (DIA), double poling kick (DK), double poling (DP), miscellaneous (MISC). The columns represent the cycles labelled as one of the four classes by video proof (gold standard), while the rows represent the cycles classified to each of the four classes by the algorithm. The diagonal represents the cycles correctly classified, the bottom row represents the specificity for each class and the right column represents the precision



classification precision by implementing further sub-techniques. Table 4 shows that all sub-techniques were used during validation and that the sensitivity for DP, DIA and DK were excellent. It also shows that the miscellaneous class was much higher (24% of cycles instead of ~ 7% of

cycles) for participant 3 than for the other skiers. This is due to the fact that the course in Natrudstilen was a competitive XC arena with sharp curves and steep hills, demanding the skiers to use techniques other than the three main sub-techniques; this was not the case at Sognefjellet.

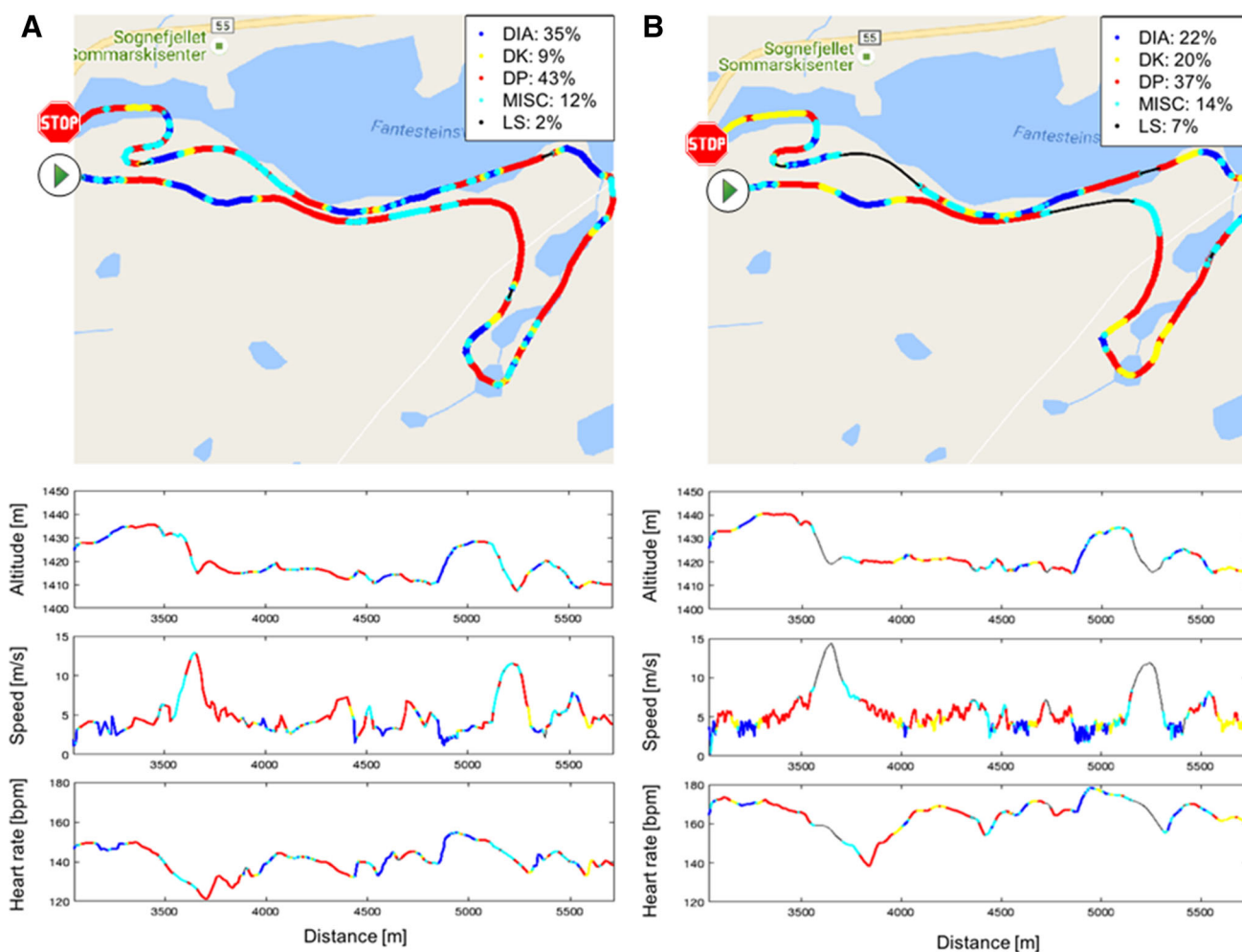


Fig. 6 Map, altitude, speed and heart rate with sub-technique classification [diagonal (DIA), double poling kick (DK), double poling (DP) and other techniques (MISC)] of **a** an amateur (participant 4) skier and **b** professional skier (participant 5) while skiing with the classical technique at high intensity in mountain

As an overall interpretation of the confusion matrices, the sensitivity and specificity for DP, DIA and DK were excellent, but there was some confusion regarding the cycles classified or labelled as MISC. This is as expected since the cycles labelled or classified as MISC fall outside the current assumptions defined for the classification algorithm.

3.3 Feasibility of sub-technique identification in skiers' training

In this sub-section, we exemplify how sub-techniques characterization can be used by comparing two different skiers while skiing at moderate and high intensity. Maps showing sub-technique distribution with corresponding altitude, speed and heart rate versus distance while skiing with high intensity in mountainous terrain at Sognefjellet

terrain. Periods with one or more missing channels (LS) due to sensor dropouts are indicated with black lines. Numbers of the overall distribution of sub-techniques (in fraction) are displayed in the legends of the maps

for one amateur (participant 4, Fig. 6a) and one professional (participant 5) are displayed in Fig. 6b. The professional skier had two periods when one or more channels had dropouts, shown as black lines and marked as lost sensor data (LS). Both periods were during steep downhill (i.e., it would have been classified as MISC) when the skier had his arms tight to the body. Both the amateur and the professional skier were generally using DIA uphill, DP in flat terrain and MISC downhill. The highest speed was when using DP or MISC, and the lowest speed was when using DIA and DK. Overall, the professional skier was using more DK and less DIA than the amateur skier, which is as expected.

In Table 5, the information from the high-intensity session has been quantified and compared with moderate-intensity sessions in the exact same track. There is a clear difference between the moderate and high intensities for

Table 5 Sub-technique classification [diagonal (DIA), double poling kick (DK), double poling (DP)] and race characteristics of an amateur (participant 4) and a professional (participant 5) skier while skiing with the classical technique at moderate and high intensity in mountain terrain

Parameters	Participant 4		Participant 5	
	Moderate intensity	High intensity	Moderate intensity	High intensity
Racing time	13:13	11:55	11:23	09:40
Racing distance (m)	2760	2760	2790	2790
Distance climbed (m)	74.2	75.9	91.8	90.4
Mean speed (m/s)	3.5	4.1	4.1	4.8
Mean heart rate (% _{max})	72	84	82	89
Frequency (Hz)	0.76	0.83	0.68	0.75
Frequency DIA (Hz)	0.86	0.95	0.77	0.86
Frequency DK (Hz)	0.73	0.81	0.65	0.71
Frequency DP (Hz)	0.71	0.78	0.65	0.72
DIA (% Time)	38	35	28	22
DK (% Time)	8	9	14	20
DP (% Time)	34	43	35	37
MISC (% Time)	13	12	15	14
LS (% Time)	7	2	8	7

MISC other techniques than DIA, DK and DP, *LS* periods with less data, dropouts of at least one channel, % *Time* percentage in time/samples

both participants. The high-intensity run had, as expected, shorter duration time, higher speed, higher mean heart rate and higher frequency compared to the moderate-intensity run. The amateur participant was using more DP and less DIA in the high-intensity run compared to the moderate-intensity run, while the use of DK was similar. The professional skier was using more DK and less DIA during high-intensity compared to the moderate-intensity run. Both these findings were expected since DP and DK are normally used at higher speeds than DIA. When increasing intensity, also speed increases and a larger distribution of “high-speed” sub-techniques are employed. Figure 7 shows the altitude and accumulated time loss for the amateur skier (participant 4) compared to the professional skier (participant 5). The amateur skier was continuously losing time compared to the professional skier, but more during uphill than downhill terrain.

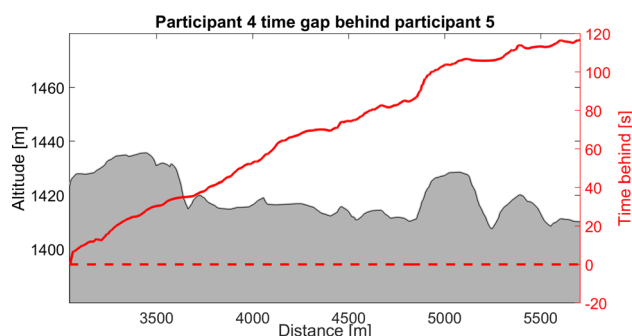


Fig. 7 Accumulated time gap (red) for the amateur skier (participant 4) compared to the professional skier (participant 5) and height altitude while skiing the same segment in high intensity

4 Discussion

In this study, we demonstrate the possibilities of using a multi-sensor system with time-synchronized heart rate, multiple triaxial IMUs as well as global position data to detect sub-technique distribution and detailed micro-parameters, such as timing between different body parts and repeatability, amplitude and sharpness in the cyclic pattern while XC skiing in the classical technique on snow. A bottom-up approach based on knowledge and the most obvious and intuitive patterns was used to develop an algorithm based on the correlation between the angular velocity of arms and legs to classify the three main classical sub-techniques. This approach showed excellent sensitivity and precision of 99–100%, for both amateur and professional skiers. Subsequently, this information was connected to the skier’s position as well as to the corresponding speed, incline and heart rate.

4.1 Development of a flexible multi-sensor system for measuring movement in cross-country skiing

The IsenseU-Ski multi-sensor system, developed specifically for this study, uses a total of seven sensor units that can easily be attached/detached on various parts of the body providing movement data with sufficient quality for subsequent analyses of detailed technique parameters in XC skiing. A multi-sensor system has the potential to reveal features that are quantified indicators of technique performance. To monitor these features in deeper case studies and thereby identify the main underlying

mechanisms may be a helpful tool as athletes strive to improve their technique. Single sensor systems, most commonly used in field conditions previously [10–12], can be useful for sub-technique classification, but do not have the same potential for technique evaluation as a multi-sensor system. Sakurai et al. [13, 14] used four accelerometers placed on hands and skis showing that they were able to classify the main sub-techniques of the skating technique, but did not study details in phase differences, timing or technique characteristics. In addition, Myklebust et al. [19] used a wired system with five accelerometers (Plux: <http://biosignalsplux.com>) taped to the hip, poles and ski boots to study differences in skating sub-techniques. Such wired systems, like Plux or Xsens (<https://www.xsens.com>), do not have limitations with regard to the wireless data acquisition, but they constrain the location of sensors and are more complex to attach/detach.

The advantage of a flexible system like IsenseU-Ski, compared to commercial systems used by others, is control of the raw data and all steps of the processing in the embedded software. Thus, we can change parameters like sampling rate, raw data filtering, signal processing and calibration according to the requirements. This is highly preferable to designing and running different protocols, and it allows the measurement of macro parameters, e.g., sub-technique classification, over long periods of time due to less power consumption, as well as high-resolution parameters over shorter times, e.g., measuring differences in the DP technique between two different skiers. Since the calibration, which is dependent on the position/orientation of the sensor, can be adopted, the sensors can be shifted and placed on other locations on the body or onto equipment like skis, boots and poles. Also, other commercial sensors (for example, oxygen saturation, non-invasive lactate or breathing sensors) can be synchronized with our system to get better control over the power used by the skier. In this study, the data analyses were post-treated and the data were available immediately after the sensor data were uploaded. However, the information can, in principle, be presented online as long as Wi-Fi or mobile connection (3G, 4G) is available.

Our study has been done outdoors on snow under various conditions, while most other studies have been performed indoors in the laboratory on treadmills [19] or outside on roller skis [12–14]. In addition, time-synchronized sensor data from seven locations opens up for more detailed analyses outside on snow than those previously performed by others. Various features related to the cyclic pattern, for example cycle similarity/repeatability for each sensor, cycle peaks and cycle peak timing/phase, can be extracted and used for evaluating technique quality in different terrains and conditions. There is currently a lack of information on technique quality measures when

training or competing in the field during XC skiing, and feature extraction from our system may be used as a tool for such purposes. When such features are validated, they can be further used to characterize and improve the technique for both amateurs and professional skiers or to see the effects of changes in equipment.

Validation of algorithms and systems for characterizing XC skiing is time consuming, since it involves manually getting ‘the proof’ from a video. Since the precision and sensitivity of IsenseU-Ski were excellent, this system has the potential of replacing the video proof and is thereby a valuable tool for validating more simple single-sensor systems and their ability to classify sub-techniques in classical XC skiing.

4.2 Validation of sub-techniques

The implemented algorithm validly detected the three main classic sub-techniques, DIA, DP and DK, for both amateurs and professionals with an excellent sensitivity and precision of 99–100%. The results showed that there were only two cycles that were misclassified in the main sub-techniques (DIA, DP and DK) for the six datasets evaluated. Participant 1 had one cycle classified as DK that had been labelled as DP. In that case, the algorithm was using a window of data that contained roughly two cycles. This particular cycle was a DP cycle with a lane change that contained a DK cycle before and after, i.e., some of the pre- and post-samples were used in the classification of the cycles within. This resulted in an overweight of samples within the cycle definition classified as DK (20/28). Participant 7 had one cycle classified as DP that was labelled as DK. In this cycle, the test participant used a left leg kick, but this was not seen because it was dropped out in samples from the left leg sensor.

The algorithm only used data from the gyroscope and features from the sensor’s axis perpendicular to the athlete’s sagittal plane; see Fig. 1. This means that techniques characterized by motion around the axis perpendicular to the coronal plane are not detected or evaluated by the current implementation. Thus, direction-change techniques were not observed, detected or classified. Techniques commonly used outside the tracks like herringbone technique and DP through turns or tracks changes with path correcting leg work are not specifically addressed or grouped in the implementation. Due to the algorithm definition, these will typically be classified as DIA and DP. However, the human observer would label these cycles as MISC. This explains the confusion for the MISC class seen in the confusion matrices in Fig. 5.

In the literature, two studies have reported on automatic classification of classical sub-techniques [11, 13], while Stöggl et al. [12] and Sakurai et al. [14] classified sub-

techniques in the skating technique. The findings from Marsland et al. [11] report an overall classification rate of 83% for DIA, DP and DK. They have, however, reported that 39.7% of the misclassified cycles were due to incorrect turn classification. Sakurai et al. [13] reported 98.5% accuracy of the total classification of DIA, DP and DK on roller skis. Since we only included and evaluated the three main classical sub-techniques in our algorithm, the precision of the two methods cannot be directly compared. Also, the percentage of time using the MISC class will be highly dependent on both the skills of the skier and the terrain. A beginner will have more slipped kicks and unidentifiable technique cycles than a highly skilled skier. Our data support this: in a relatively flat terrain without sharp turns, the MISC class was down to 0%, while in competitive XC arenas the MISC class was around 24%.

The presented classification method was based on a bottom-up approach by manually exploring the data selecting features based on knowledge and the most obvious and intuitive patterns. The algorithm represents an early stage in the process of exploring and making a detailed model technique identification and characterization. A more general study, including multivariate analysis and statistics for identifying the main descriptive features from all the sensors and sensor channels, should be considered to reduce the need of sensors and classify sub-techniques other than DP, DIA and DK. Rules for these techniques can, however, be added in a modular way by applying features that catch sideways leg work in a similar way as presented for the DK technique. Treating these techniques as separate sub-techniques is expected to greatly improve the classification of sub-techniques now treated as MISC, e.g., herringbone, turning techniques, changing tracks and so on.

4.3 Sub-technique identification in different terrains

This is the first time sub-technique classification in XC skiing has been linked to global position data on snow to show the distribution of sub-techniques in different terrains and at varying conditions. Sakurai et al. [13] automatically identified the sub-technique of classical skiing, but their study was performed on roller skis and was only linked to the inclination and skiing velocity from the position data, not creating a detailed distribution of sub-techniques linked to the skier's position from GNSS data. In addition, there are few other reported studies using IMUs in XC skiing [11, 12, 14], and their data has not been synchronized with position data. Also, most other studies using IMUs in XC skiing were performed indoors on roller skis. Our work is the first to report the use on multiple triaxial IMU data measured outdoors on snow in different terrains and during varying conditions.

The link between classified sub-techniques and data from GNSSs is important, since the choice of sub-techniques and kinematics are clearly influenced by speed and incline. Our system makes it possible to detect differences in sub-technique distribution between high and moderate intensity and between skiers of different performance levels. Hence, a distribution of these sub-techniques in skiers' daily training and competitions would provide a unique insight into the technical and tactical aspects that could be used for further development of their technique and performance.

5 Conclusion

This new system for measuring and analysing XC skiing technique is comfortable and flexible and can wirelessly measure a large amount of synchronized movement data that are valuable for subsequent micro and macro analyses of XC skiing techniques. By using our bottom-up approach, based on knowledge and the most obvious and intuitive patterns, we developed an algorithm where correlation measures between IMUs on the arms and legs classified sub-techniques. This algorithm could automatically identify the three main classical sub-techniques in XC skiing with excellent sensitivity and a precision of 99–100%, for both amateur and professional skiers. Our algorithm used data from the gyroscope and features from the sensor's axis perpendicular to the athlete's sagittal plane, which was appropriate for the detection of these three techniques. However, motion around the axis perpendicular to the coronal plane is not detected or evaluated by the current implementation. This might limit the detection of other sub-techniques such as herringbone in classical skiing or the different skating techniques. The main challenge with the current system is related to dropouts in signals due to limitation in wireless technology.

Uniquely, this study is the first to detect and link sub-techniques in XC skiing to global position data and to provide a distribution of sub-techniques in different terrains. Such information gives a unique insight into the technical and tactical aspects of skiers' daily training and competitions, thereby providing a valuable tool for coaches and athletes. For example, the amount of time spent on various sub-techniques during different types of training (e.g., continuous low-intensity training or high-intensity interval training) is of high interest in this connection. Furthermore, the individual skiers' speed or work rate spectra in the utilization of different sub-techniques, as well as the specification of typical transition points between sub-techniques, would provide valuable information. This would enable a comparison of these aspects between training sessions performed at different track

profiles and external conditions and competitions, and between roller skiing versus on-snow training. Overall, this information allows for better understanding of the training load and technical solutions performed, which subsequently allows for better coaching and future planning of training. In addition, competition analyses showing where and why skiers lose or gain time compared to competitors could be of high interest for athletes, coaches and even spectators and media in the future.

Acknowledgements This work is part of the emPower Project, an IPN Project in the BIA Program supported by the Norwegian Research Council and Madshus, Project Number 245622. We thank the skiers for their participation in the study and Madshus for technical support during field tests.

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