

## RESEARCH ARTICLE

# Wearable Sensors and Computational Intelligence in Alpine Skiing Analysis

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics committee of the Neurological Center at Rychnov n. Kn., Czech Republic.

**ABSTRACT** The integration of wearable sensors with artificial intelligence forms the base for analyzing physical activities through digital signal processing, numerical methods, and machine learning. Computational intelligence and communication technologies enable personalized monitoring, training, and rehabilitation, with applications in sports, neurology, and biomedicine. This paper focuses on motion analysis in alpine skiing using real accelerometric, gyroscopic, positioning, and video data to evaluate ski movement patterns. The proposed methodology employs functional transforms to estimate motion patterns and utilizes artificial intelligence for signal segmentation and feature classification related to lower limb movement. Machine learning results indicate differences in energy distribution before and after ski turns and demonstrate the feasibility of classifying associated motion patterns with accuracies of 98.1% and 90.7%, respectively, using a two-layer neural network. The interdisciplinary application of computational intelligence in this domain enhances motion analysis, injury prevention, and performance optimization. This study highlights the unifying role of digital signal processing, which uses similar mathematical tools across various applications.

**INDEX TERMS** Computational intelligence, wearable sensors, accelerometers, gyroscopes, physical activity monitoring, alpine skiing.

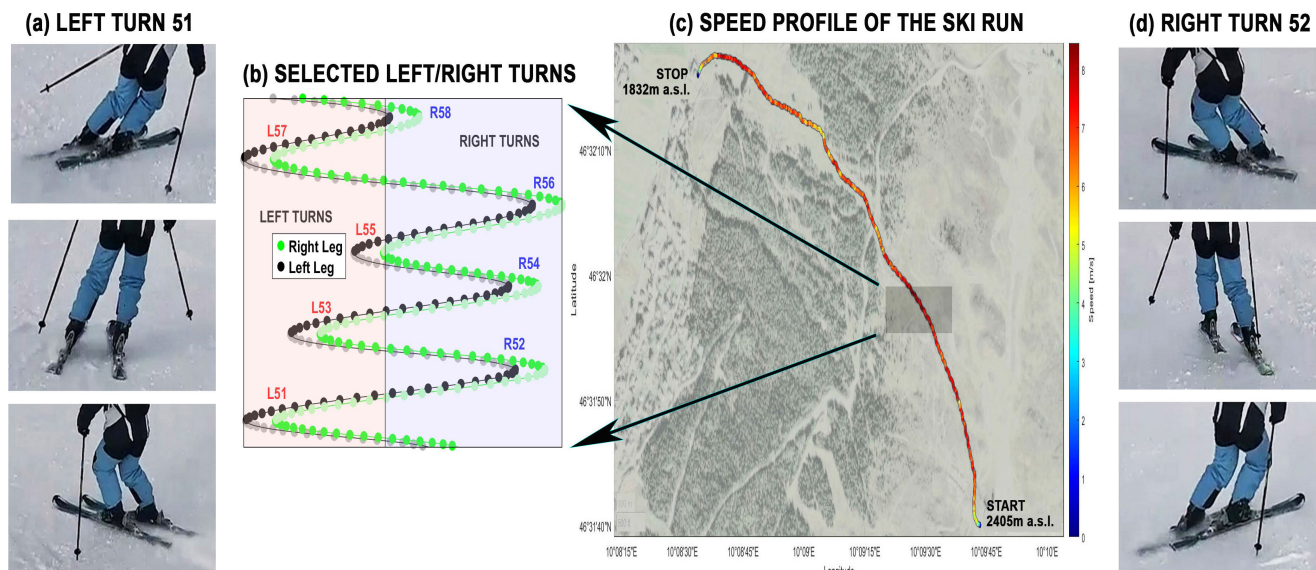
## I. INTRODUCTION

Wearable sensors combined with artificial intelligence (AI) can significantly enhance the analysis of motion patterns using general digital signal processing techniques, numerical methods, and machine learning algorithms [1], [2]. Computational intelligence (CI) methods are employed for personalized physical activity monitoring, training, and motion modelling. Applications include the evaluation of various physical activities in rehabilitation, as well as the detection of neurological and biomedical disorders. In the

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context of downhill and cross-country skiing, numerous studies focus on analyzing skiing trajectories, tracking the evolution of body mass center over time, and optimizing motion techniques.

Sensor systems [3], [4], [5], [6], [7] play an important role in collecting real-time physiological and biomechanical data during motion, including alpine skiing [8], [9], [10], [11]. Inertial Measurement Units (IMUs), which include accelerometers and gyroscopes, are used to analyze skiing kinematics [12], [13], tracking motion, balance, and turning points. The Global Navigation Satellite System (GNSS) [14] provides information on position, trajectory, and speed, which can be integrated with data from camera



**FIGURE 1.** The outline drawing of the ski route presenting starting point at the altitude of 2405m a.s.l. and the final destination at the altitude of 1832m a.s.l. presenting (a,d) selected left and right ski turns, (b) a ski run section with time instants difference of 0.1s and changes of activities of the left and right legs during turns, and (c) the speed profile of the selected ski run.

systems [15]. Biomedical sensors collect physiological data such as heart rate (HR) and oxygen concentration, among other parameters. Additionally, environmental sensors can be utilized to correlate motion strategies with external skiing conditions. Wireless communication systems facilitate data transmission, time synchronization of acquired signals, and the organization of data in a database system for mathematical processing.

Mathematical methods serve as essential tools for analyzing motion patterns. In the case of skiing data processing, these methods include numerical techniques and digital filtering for data preprocessing, functional transforms for extracting frequency component evolution—often utilizing discrete Fourier and wavelet transforms—and machine learning algorithms for motion pattern identification and classification. Correlating data acquired from optimally positioned body sensors [16], synchronizing signals, and applying deep learning-based processing [11] enable the tracking of motion habits and physical activities.

Augmented reality and digital twins are increasingly used for motion modeling and analysis. Specific studies focus on the interaction between skis and snow [17], as irregularities on ski slopes significantly contribute to vibrations and affect skiing techniques. Associated simulation models help understand the principles of ski vibrations, determine optimal materials to enhance performance, and prevent injuries in alpine skiing. Other research areas include ski run optimization [18], [19] and investigations into the transmissibility of vibrations from skis to the lower back [20], [21] and head using power spectral analysis of observed data.

Applications extend to physical activity monitoring, vision-based skiing evaluation [22], injury situation analysis [23], post-surgical recovery assessment, and rehabilitation

planning support. Real-time sensor applications aid in learning balance and turning techniques during skiing training. Computational intelligence methods for motion segmentation and classification in alpine skiing use IMU data for analyzing edge angles and radial forces. GNSS-based research [24], [25] focuses on analyzing geographical data, while further studies examine the kinematic and kinetic patterns of turns in alpine skiing [21], [26], skiing technique analysis, and skiing pattern recognition [27], [28].

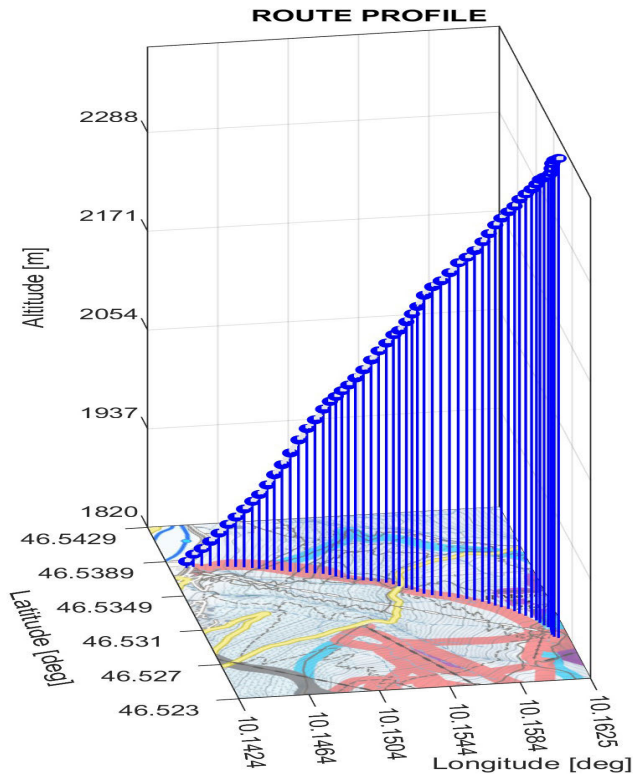
The rest of the paper is organized as follows: Section II describes the proposed methodology, including data acquisition and an overview of signal processing methods. Section III presents the results of skiing pattern analysis based on three experimental runs conducted under real conditions. Section IV discusses the findings, and Section V concludes the paper with remarks on potential future research directions.

## II. METHODS

The dataset comprises data collected from wearable sensors, including a GNSS receiver and a three-axis accelerometer and gyroscope, used for detecting skiing turns [29]. The GNSS receiver records terrestrial data such as longitude, latitude, and altitude.

A detailed description of the observations is available on IEEE DataPort (<https://dx.doi.org/10.21227/qebb-nf33>, Skiing Data Analysis) for further investigation. This repository contains the complete set of skiing data recorded by the authors. Additionally, a graphical abstract of the paper is included in the repository.

All procedures involving human participants complied with the ethical standards of the institutional research committee and adhered to the 1964 Helsinki Declaration and its subsequent amendments.



**FIGURE 2.** Spatial plot of the skiing route on the real mountain slope presented in the Matlab mapping environment based on the GNSS geographical data acquired by the Garmin sensor.

**A. DATA ACQUISITION**

Figure 1 illustrates the main concept of skiing data acquisition under real mountain conditions during ski runs on a 2151m long slope with an altitude difference of 573m, starting at an altitude of 2405m above sea level. The experiments involved an average of 154 ski turns per run. Signals recorded during the experimental runs include data from GNSS, accelerometric, and gyroscopic sensors. Figure 1(b) presents a selected section of a ski run, highlighting positioning differences of 0.1s and variations in left and right leg loads during turns. Selected left and right ski turns are shown in Figs 1(a) and 1(d), depicting the skier’s position before and after a turn. Figure 1(c) displays the speed profile recorded during a specific experiment.

Figure 2 shows the skiing route on an actual mountain slope, visualized using the Matlab mapping environment and based on GNSS geographical data recorded by Garmin sensors. Animation of this route is presented in the video abstract [30]. Accelerometric and gyroscopic data were collected using WITmotion sensors, which were attached above the ankles of both legs during the skiing experiments.

The recorded database consists of motion signals acquired at a sampling frequency of 100Hz, with wireless data transmission to a tablet carried by the examined individual on the back. Geographical and speed data were collected using the Garmin system at a sampling frequency of 1Hz.

Simultaneously, video data were recorded using a GoPro camera. These sensors were utilized to analyze skiing patterns under real conditions, identify turning points, and examine detail variations in leg loading during alpine skiing on a natural mountain slope.

The proposed methodology utilizes both system monitoring via selected sensors, signal transmission, and data processing in the computational environment of Matlab 2025a (MathWorks, Natick, MA).

**B. SIGNAL PROCESSING**

Data processing procedures are intrinsically linked to the characteristics of the sensors used for data acquisition. Accelerometric and gyroscopic data for each experiment were captured by tri-axial sensors positioned on specific parts of the body (above ankles of the left leg and right leg). This data generated three sequences  $\{s_x(n), s_y(n), s_z(n)\}_{n=0}^{N-1}$  for each location. Typically, the modulus of these sequences for  $n = 0, 1, \dots, N - 1$  was calculated using the following relation:

$$s(n) = \sqrt{s_x(n)^2 + s_y(n)^2 + s_z(n)^2} \tag{1}$$

with their mean value  $\bar{s} = \sum s(n)/N$ .

Signal preprocessing included digital filtering of the given data both by the median filtering of selected order and FIR filtering of order 20 and chosen cutoff frequencies. For the time synchronization of all sensors, their chip time was used together with the cross correlation method. Analysis of signals was then performed both by the discrete Fourier (DFT) and wavelet (DWT) transforms [31], [32], [33].

Spectral components were estimated by the discrete Fourier transform:

$$S(k) = \sum_{n=0}^{N-1} (s(n) - \bar{s}) e^{-jk n 2 \pi / N} \tag{2}$$

for  $k = 0, 1, \dots, N - 1$ . The relative power  $E_p(d)$  for each data segment  $d$  in the frequency band  $\langle fc_1, fc_2 \rangle$  was then evaluated for each sensor position  $p$  by relation:

$$E_p(d) = \frac{\sum_{k \in \Phi_w} |S(k)|^2}{\sum_{k=0}^{N/2} |S(k)|^2} \tag{3}$$

where  $\Phi_w$  denotes the set of indices for the spectral components within the selected frequency range  $\langle fc_1, fc_2 \rangle$ .

Scaling analysis allowed the estimation of energy on the selected level. In principle this approach is based on the use of a mother function  $h(t)$ , discretized by parameters of dilation  $m$  and translation  $k$ :

$$h_{m,k}(t) = \frac{1}{\sqrt{2^m}} h(2^{-m}t - k) \tag{4}$$

Resulting set of wavelet functions can be delated and translated to view signals from the detail and global point of views. This process was done with the Daubechies DB4 wavelet function and decomposition into the third level.

The symmetry index was then estimated as the ratio of energy for the left and right side of the body by relation:

$$C(d) = \frac{E_{Left}(d)}{E_{Right}(d)} \quad (5)$$

This calculation was applied to each data segment  $d$  and both for accelerometric and gyroscopic data.

Spectral data features evaluated both by the DFT and DWT were then organized in the pattern matrix  $P$  and associated target vector  $T$  that specified data for classification by the  $k$ -nearest neighbour and support vector machine methods. Bayesian probabilistic method [34] was then tested as owing to its simplicity and efficiency, it can out-perform more sophisticated classification methods. Hidden Markov models (HMMs) [35], machine learning and computational intelligence methods were further applied to estimate the skiing motion symmetry. Verification of the classification methods was done by the evaluation of the  $k$ -fold cross validation method.

### III. RESULTS

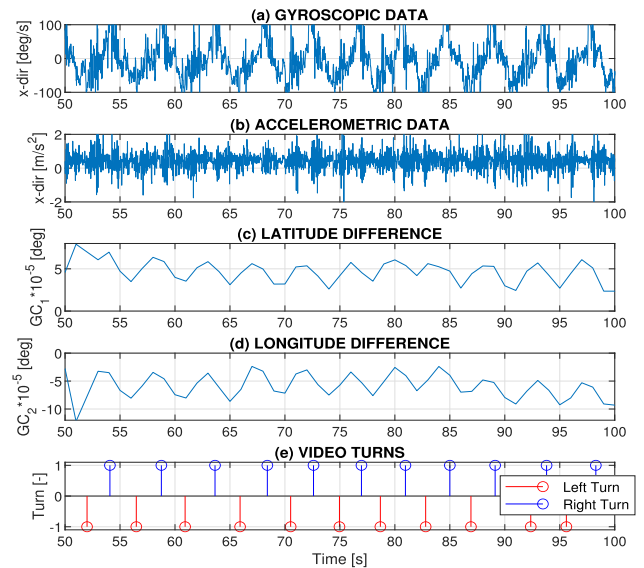
Processing of signals acquired during ski runs by video, accelerometric, gyroscopic, and Garmin motion sensors includes the following steps:

- 1) Data preprocessing using digital filters, possible interpolation, and statistical analysis.
- 2) Detection of ski turns from geographical, gyroscopic and video data.
- 3) Time synchronization of data from different sensors.
- 4) Detection of features before and after ski turns estimated from sensors on the left and right legs.
- 5) Analysis of motion patterns using artificial intelligence tools and evaluation of the skiing technique.

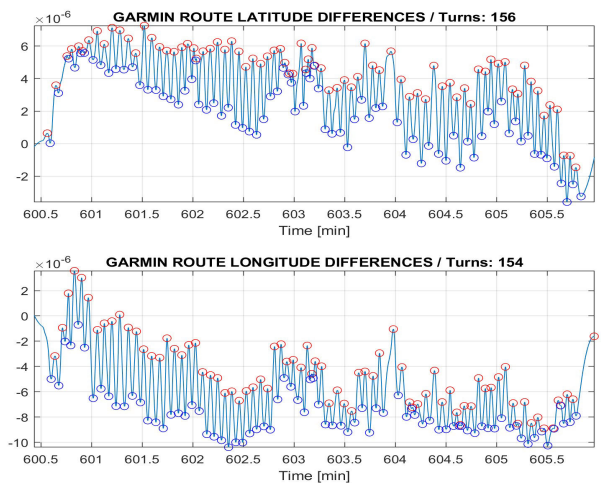
The initial time synchronization of all sensors was performed by analyzing data acquired from motion sensors and validated using the cross-correlation function. The correspondence between turn points estimated from gyroscopic, Garmin, and video data was verified through the cross-correlation coefficient, which exceeded 0.99 for all pairs of signals.

Figure 3 displays selected signals acquired over a 50-second time segment, recorded from the right leg. Figures 3(a,b) present gyroscopic and accelerometric data in the horizontal x-direction. Additional motion data recorded in the y- and z-directions were used to evaluate their magnitude, ensuring independence from the orientation of individual sensors. Figures 3(c,d) illustrate latitude and longitude variations based on the Garmin Geographical Coordinate System (GCS) and their changes during ski turns. Figure 3(e) shows the time instants of left and right ski turns as recorded by the video camera. Preprocessing of these data involved the removal of gross errors using a three-point median filter and spline interpolation for refining the geographical data.

A more detailed analysis of geographical coordinates used to detect all ski turns in a selected experiment is presented in Fig. 4. The sign of these differences enabled the identification



**FIGURE 3.** Signals acquired during a time segment 50s long presenting (a,b) gyroscopic and accelerometric data in the horizontal x-direction, (c,d) latitude and longitude differences in the geographical coordinate system, and (e) times of the left and right ski turns recorded by the video camera.



**FIGURE 4.** Difference of latitude and longitude records acquired during a selected experiment used for location of ski turns.

of right and left turns on the ski slope. Since longitude and latitude differences can be associated with distances at a given position, it was possible to estimate speed variations in two orthogonal directions. Figure 5 illustrates a selected segment of GNSS speed components along the latitude and longitude directions, highlighting the ski turning points for the selected experiment.

Table 1 presents the evaluation of three ski runs on a 2151m long slope with an altitude difference of 573m (ranging from 2405m to 1832m above sea level). Each run included an average of 154 turns, with an average duration of 1.94 seconds per turn. During all experiments, GNSS, video, and motion signals were recorded. Accelerometric and

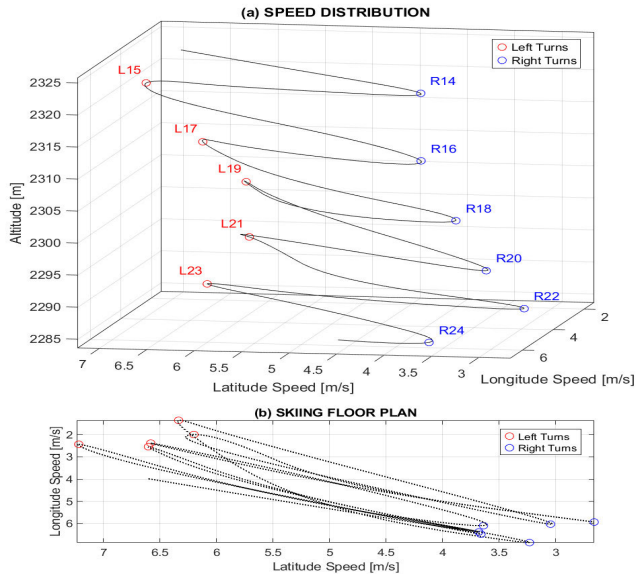


FIGURE 5. Segment of the skiing route presenting (a) GNSS speed components in the latitude and longitude direction showing the skiing turning points and (b) skiing floor plan.

TABLE 1. Comparison of energy ratio for the time band of 1.50s before and after turn points for individual legs (Left, Right), percentage of correct distribution (Sym) of energy between legs for three runs and energy evaluated by the DFT in the range of (10, 30) Hz and the third level of the DWT decomposition of the accelerometric signals acquired with the sampling frequency of 100 Hz.

Exp.	Turns	DFT Evaluation [%]			DWT Evaluation [%]		
		Left	Right	Sym	Left	Right	Sym
1	146	67.8	66.1	50.4	73.9	72.2	43.5
2	160	60.5	62.0	52.7	78.3	82.0	48.1
3	156	50.4	48.0	46.4	76.8	80.8	52.0
Mean	154	59.6	58.7	49.8	76.3	78.3	47.9

gyroscopic signals were acquired from sensors attached to both the left and right legs, with a sampling frequency of 100Hz in all cases.

The analysis of ski turns is based on the energy ratio evaluation over a 1.50-second time window before and after turn points, which were detected using a video camera and synchronized with motion data for each leg. Figure 6 illustrates a selected left turn (with index 72) extracted from the first experimental ski run, focusing on the left leg. Signal segments before and after the ski turn were analyzed in both the spectral domain using the discrete Fourier transform and the scale domain using the discrete wavelet transform. For a left turn, the left leg experiences higher exposure before the turn compared to its state after the turn, whereas the energy distribution for the right leg follows an inverse pattern.

A quantitative analysis of these observations was performed by calculating the percentage ratio of spectral components within the frequency range (10, 30)Hz, evaluated using the DFT and compared with DWT decomposition up to the third level. Figure 7 presents the distribution of these motion features before and after ski turns for the entire first experimental run. The distinct roles of the left and right legs during left and right turns are clearly evident. For each feature

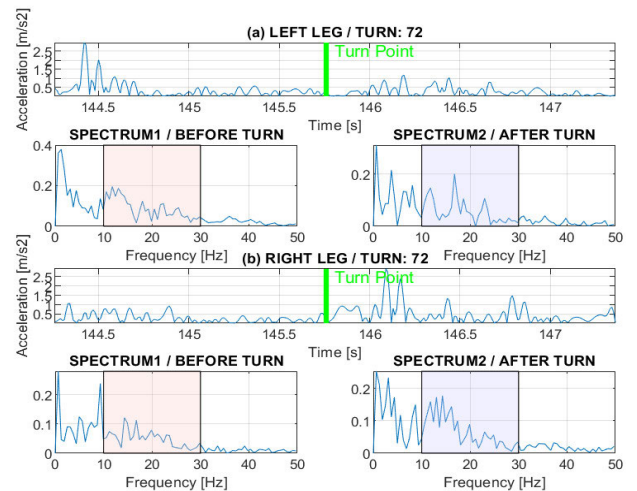


FIGURE 6. Accelerometric signals in the time range of 1.50s before and after the right turn 72 of Experiment1 presenting data with their spectra (a) for the left and (b) the right leg showing the turn point and spectral region used for energy estimation.

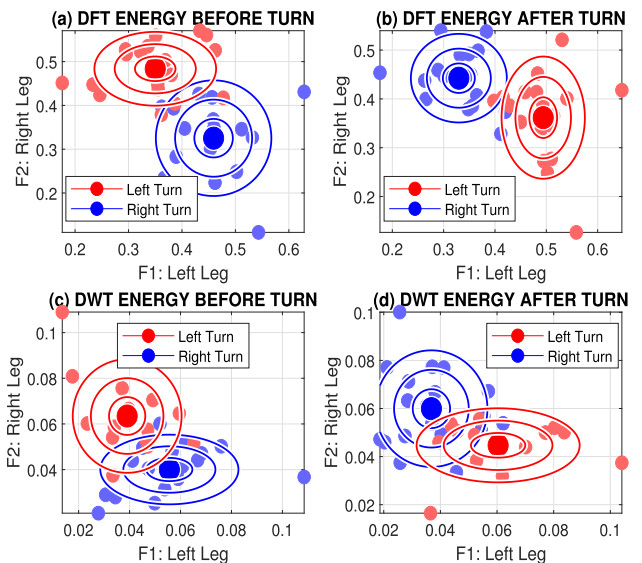


FIGURE 7. Distribution of motion features presenting energy before and after skiing turns using (a,b) spectral features using discrete Fourier transform and (c,d) wavelet domain features for the second decomposition level using discrete wavelet transform with c multiples of standard deviations for c=0.5,1 and 1.5.

cluster, the centers of gravity were determined, along with c multiples of standard deviations for c = 0.5, 1, and 1.5.

Table 2 presents the mean and standard deviations (STD) of discrete Fourier transform and discrete wavelet transform features related to accelerometric data for three experimental ski runs. It compares the mean energy values before and after ski turns for the left and right legs. The mean energy values of the left and right legs before and after ski turns exhibit opposite trends for both DFT and DWT features.

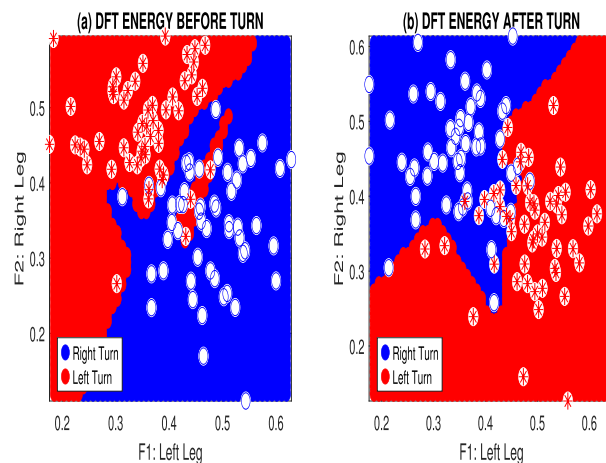
Figure 8 illustrates the mean motion DFT energy of the left and right legs before and after ski turns. Energy ratio changes during each turn correspond to shifts in the role of

**TABLE 2.** Mean and standard deviation (STD) values of discrete Fourier transform (DFT) and discrete wavelet transform (DWT) features related to accelerometric data for three experimental ski runs comparing mean values of energies before and after ski turns for the left (LL) and right (RL) legs.

Exp.	Turn	DFT mean and STD evaluation			
		Before Turn		After Turn	
		F1 / LL	F2 / RL	F1 / LL	F2 / RL
1	Left	0.33±0.09	0.46±0.07	0.44±0.06	0.33±0.06
	Right	0.48±0.06	0.35±0.08	0.36±0.08	0.49±0.05
2	Left	0.35±0.08	0.47±0.06	0.47±0.09	0.35±0.08
	Right	0.45±0.09	0.35±0.08	0.34±0.07	0.48±0.08
3	Left	0.36±0.06	0.50±0.07	0.46±0.07	0.36±0.08
	Right	0.49±0.05	0.36±0.07	0.37±0.07	0.48±0.08
Mean Left:		0.35	0.48	0.46	0.35
Mean Right:		0.47	0.35	0.36	0.48

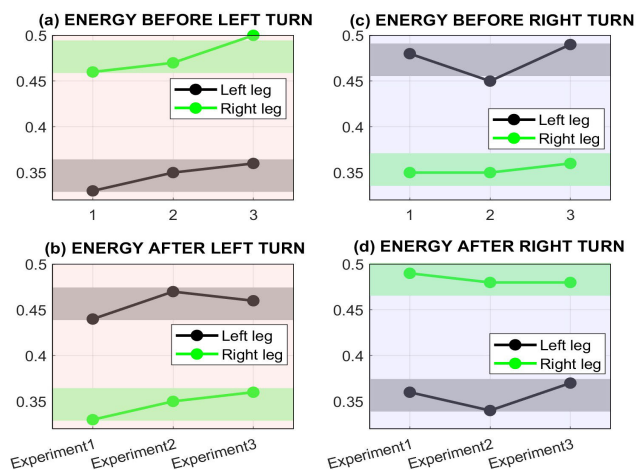
Exp.	Turn	DWT mean and STD Evaluation			
		Before Turn		After Turn	
		F1 / LL	F2 / RL	F1 / LL	F2 / RL
1	Left	0.04±0.01	0.06±0.01	0.06±0.02	0.04±0.01
	Right	0.04±0.01	0.04±0.01	0.04±0.01	0.06±0.02
2	Left	0.04±0.01	0.06±0.02	0.06±0.02	0.04±0.01
	Right	0.06±0.02	0.03±0.01	0.03±0.01	0.05±0.01
3	Left	0.04±0.01	0.07±0.03	0.06±0.02	0.04±0.02
	Right	0.07±0.02	0.04±0.02	0.04±0.02	0.07±0.03
Mean Left:		0.04	0.06	0.06	0.04
Mean Right:		0.06	0.04	0.04	0.06



**FIGURE 9.** Classification of left and right ski turns based on DFT energy estimated from the left and right leg motions presenting results (a) before ski turns (accuracy: 98.1%, cross-validation: 0.02) and (b) after ski turns (accuracy: 90.7%, cross-validation: 0.14) for 3 experimental ski runs and neural network two layer system.

**TABLE 3.** Results of classification related to the energy portion on the left and right legs before and after ski turns by the 3-nearest neighbour (NN3), support vector method (SVM), Bayesian methods, and a two layer neural network for the complete set of three experimental ski runs with classification accuracy and a ten fold cross-validation (CV) errors with the highest accuracy and the lowest cross-validation errors in bold.

Method	Before Turns		After Turns	
	Accuracy [%]	CV	Accuracy [%]	CV
NN3 method	92.6	0.06	90.7	0.23
SVM method	93.5	0.05	88.9	0.13
Bayesian method	92.6	0.03	85.2	<b>0.12</b>
Neural Network	<b>98.1</b>	<b>0.02</b>	<b>90.7</b>	0.14



**FIGURE 8.** Mean motion DFT energy of left and right legs presenting situation (a,b) before and after left turn points (c,d) before and after right turn points.

the individual skis. In symmetrical downhill skiing, a similar but opposite motion pattern can be expected for each leg.

Figure 9 presents the classification of left and right ski turns based on DFT energy estimated from the left and right leg motions. The results are shown before ski turns (accuracy: 98.1%, cross-validation error: 0.02) and after ski turns (accuracy: 90.7%, cross-validation error: 0.14), evaluated using a two-layer neural network across three experimental ski runs. Similar classification results were achieved using the 3-nearest neighbour (NN3), Support Vector Machine (SVM), and Bayesian methods, as summarized in Table 3 that also presents classification accuracies and ten-fold cross-validation (CV) errors. An alternative classification based on

the use of hidden Markov models, sometimes used for activity recognition [36], and application of the Viterbi algorithm, provides the accuracy of 100% of mean value estimates of both classes for given experiments.

#### IV. DISCUSSION

This paper addresses the analysis of skiing patterns and motion monitoring under real conditions. A mathematical model is proposed to integrate and process time-synchronized accelerometric, gyroscopic, GNSS, and video sensor data. The algorithm evaluates the coefficient of symmetry and visualizes the distribution of skiing characteristics.

Results based on more than 450 ski turns recorded during three experimental runs on a 2151m long slope demonstrate how gyroscopic, geographical, and video data can be used to detect ski turn points. Accelerometric energy analysis reveals how energy distribution between the left and right legs changes during turns. Energy pattern classification shows that motion features form more compact clusters before ski turns (98.1% accuracy, cross-validation error: 0.02) compared to after ski turns (90.7% accuracy, cross-validation error: 0.14) when using neural networks.

The detection of right/left turns during skiing allows motion segmentation in real conditions. This process

enables the evaluation of movement symmetry and improvements of habits during sport activities and rehabilitation. Objective movement tracking methods include the use of GNSS, accelerometric, gyroscopic and video data. Their use, combined with physiological data, allows monitoring of the fitness level. Promising mathematical methods are based on the universality of statistical and machine learning methods and implementation of geometric and kinematic modelling, time-series analysis, Markov decision processes, optimization, and graph theory applications.

The analysis of motion patterns can benefit from the expertise of specialists in sports science, neurology, and rehabilitation. The proposed quantitative analysis, supported by data acquired from specialized motion sensors, provides an additional source of valuable information. Given the increasing availability and complexity of such data, the role of artificial intelligence and computational methods in this field is expected to grow in the future.

## V. CONCLUSION

Wearable sensors and computational methods are driving advancements in alpine skiing by enabling real-time performance analysis, injury prevention, and personalized coaching. By integrating AI-driven insights with precise sensor data, skiers of all levels can enhance their technique, efficiency, and safety on the slopes. Another significant application is in rehabilitation and evaluation of correct performance of specific exercises.

Computational intelligence enables the use of accelerometric and gyroscopic data to extract meaningful biomechanical insights into alpine skiing. The rapid progress in this field highlights the growing importance of data-driven methods for intelligent motion analysis in both sports and biomedical applications.

Future research should focus on developing ultra-lightweight multi-sensor systems with efficient, long-lasting batteries, advancing computational methods for data processing, and establishing universal performance indicators for skiing analysis. Communication technologies and multi-channel signal analysis tools provide an integrated platform for applying digital signal processing methods across various research domains.

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