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*Article*

# Inner-cycle Phases can be Estimated from a Single Inertial Sensor by Long Short-term Memory Neural Network in Roller Ski Skating

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**Abstract:** Objective: The aim of this study was to provide a new machine learning method to determine temporal events and inner-cycle parameters (e.g., cycle, poles and skis contact and swing time) in cross-country roller ski skating on the field, using a single deported inertial measurement unit (IMU). Methods: The developed method is based on long short-term memory neural networks to detect poles and skis initial and final contact with the ground during the cyclic movements. Eleven athletes skied four laps of 2.5 km at low and high intensity using skis with two different rolling coefficients. They were equipped with IMUs attached to the upper back, lower back and to the sternum. Data from force insoles and force poles were used as reference system. Results: The IMU placed on the upper back provided the best results, as the LSTM network was able to determine the temporal events with an accuracy ranging from 49 to 55 ms and the corresponding inner-cycles parameters were calculated with a precision of 63 to 68 ms. The method detected 95% of the events for the poles and 87% of the events for the skis. Conclusion: The proposed LSTM method provides a promising tool for assessing temporal events and inner-cycle phases in roller ski skating showing the potential of using a deported IMU to estimate different spatio-temporal parameters of human locomotion.

**Keywords:** cross country skiing; IMU; wearable sensors; LSTM; neural network

## 1. Introduction

Machine learning (ML) and wearable sensors are two fast evolving technologies providing new perspectives in human motion analysis. It has been shown in a relatively recent review that publications using ML on human movement biomechanics increased exponentially since 1996, for a total of 129 publications in 2017. In these studies, predictive classification and regression tasks were used in 80.6% and 11.6% respectively, while data mining (e.g., clustering tasks) was used in 7.8% of the studies [1]. Out of them, only three were using wearable sensors for movement patterns classification [2–4].

In sport science, wearable sensors are used to analyse performance and technique in ecological conditions [5]. Recently, neural networks have been developed to determine cross-country skiing sub-technique in classical style using gyroscope data from the wrist to determine cycles and accelerometer on the chest to perform the classification [6]. For the skating style, multiples IMUs were used to determine mechanical power using a long short-term memory (LSTM) recurrent neural network [7]. Measurements of the head position that could be measured using a differential global navigation system was used to

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train a neural network classifier to determine the skating sub-technique [8]. Neural networks were also used to estimate knee join force and moments during sport motions, using two IMUs placed on the leg [9,10]. With the same objective of determining joint angles, joint moments, and ground reaction force in walking and running, a convolutional neural network (CNN) was trained using both real and simulated data using multiple IMUs [11]. An estimation of the loading rate in running was also performed based on CNN, using a set of five IMUs to find the optimal sensor placement. The IMU placed on the shank provided the best outcome, and adding supplementary IMUs did not improve the model [12]. A more formal approach provided a method to automatically select the best combination of sensors to provide segmentation of locomotion phases using support vector machines and other classifiers [13]. Determining inner-cycle phases of gait in children with gait disorder provided promising results with LSTM recurrent neural network, using 3D motion camera system and focusing on markers placed on the foot of the patients [14].

Based on these recent studies, it seems that ML methods can adequately determine parameters using sensors that are placed close to the point of interest (e.g., the shank to determine the loading rate of the leg). Nevertheless, real life applications sometimes need some adjustments, as a perfect setup is usually not possible to achieve. Moreover, athletes usually do not want to be equipped with extensive equipment that can interfere with their performance. Several wearable devices such as cardio-frequency belts or GNSS-IMU sensors placed on the upper back are already used by numerus athletes to monitor their training and performance. Therefore, methods focusing on a single point have been developed [8,15]. In running, an IMU placed on the sacrum was used to predict peak vertical ground reaction force, impulse and contact time [16], but these parameters could also be determined using a traditional approach [17]. In cross country roller skiing on a treadmill, IMUs placed on the skis and poles were used to detect temporal events in classical style [18] and in skating style with IMUs placed on skis and wrist [19]. Finally, the same sensor configuration was used while roller ski skating in the field [20]. As highlighted previously, the usability of such setups for technique and performance analysis is limited, and there is a need for a simplified IMU configuration.

Therefore, the aim of this paper was to determine temporal events and estimate inner-cycle phases during roller ski skating in the field, using an LSTM machine learning method on data from a single deported IMU. Different sensor's positions were tested to assess the accuracy of the developed algorithms and find the best sensor configuration. We hypothesized that deported IMUs can provide an accuracy with the same order of magnitude as sensors placed directly on the segment of interest. A second hypothesis was that an IMU placed on the upper body will be more accurate to determine the events on the poles and an IMU placed on the lower back will be more accurate to determine the events on the skis.

## 2. Material and Methods

### *2.1. Participants*

Nine athletes of regional level (7 men, 2 women) participated in the study. The participant's characteristics were as follows: ages of 27.9 ± 6.9 years, body heights of 180 ± 6 cm, body masses of 74.2 ± 5.5 kg. The Regional Committee for Medical and Health Research Ethics waives the requirement for ethical approval for such studies. Therefore, the study was done in accordance with the institutional requirements and in line with the Helsinki declaration. Approval for data security and handling was obtained from the Norwegian Center for Research Data ahead of the study. Prior to the data collection, all skiers provided written informed consent to voluntarily take part in the study. The skiers were informed that they could withdraw from the study at any point in time without providing a reason for doing so.

### *2.2. Experimental setup*

The protocol was performed on a 2.5 km asphalt road loop in Holmenkollen, Norway (Figure 1). The skiers used poles of their individually chosen lengths, equipped with force grips recording at 100 Hz (Proskida, Whitehorse YT, Canada). All skiers wore their own skating cross country boots equipped with force insoles recording at 100 Hz (Loadsol, Novel, Munich, Germany). Two pairs of roller ski (Swenor, Sarpsborg, Norway) with Type 1 and Type 3 wheels (low and high friction coefficient) were used during the session. Two IMUs (Physilog 5, GaitUp SA, Lausanne, Switzerland), each composed of a 3D accelerometer and a 3D gyroscope with a sampling frequency of 512 Hz were mounted using belts on the sternum and on the sacrum, respectively (Figure 2). Another sensor including a GPS, a 3D accelerometer, and a 3D gyroscope, recording at 100 Hz was also placed on the upper back using a dedicated vest (Optimeye S5, Catapult, Prahran, Australia).

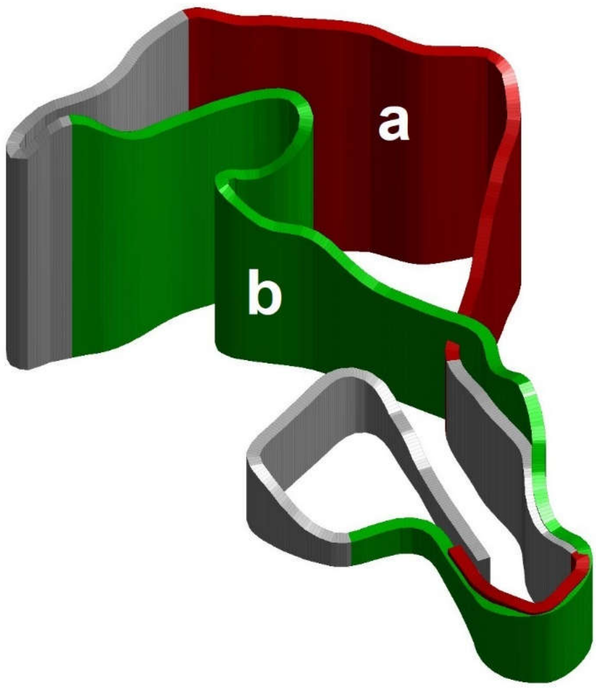


**Figure 1.** Tri-dimensional representation of the experimental track obtained using the Global Navigation Satellite System. Uphill are represented in red (a) and downhill in green (b).

Synchronization between the two Physilog 5 IMUs was performed internally using a radio signal, the synchronization between the IMUs, the force grips, the force insole, and the Optimeye S5 device was performed manually, using a dedicated pole plant and a jump at the beginning of each trial.

The experiment consisted of a 5-min warm-up on the roller skis, followed by two laps of 2.5 km at low intensity, each lap with a different pair of skis (low or high friction coefficient), chosen randomly. Then, two laps at high intensity were performed with the two different pairs of skis. Recovery time between the two laps was set to two minutes.

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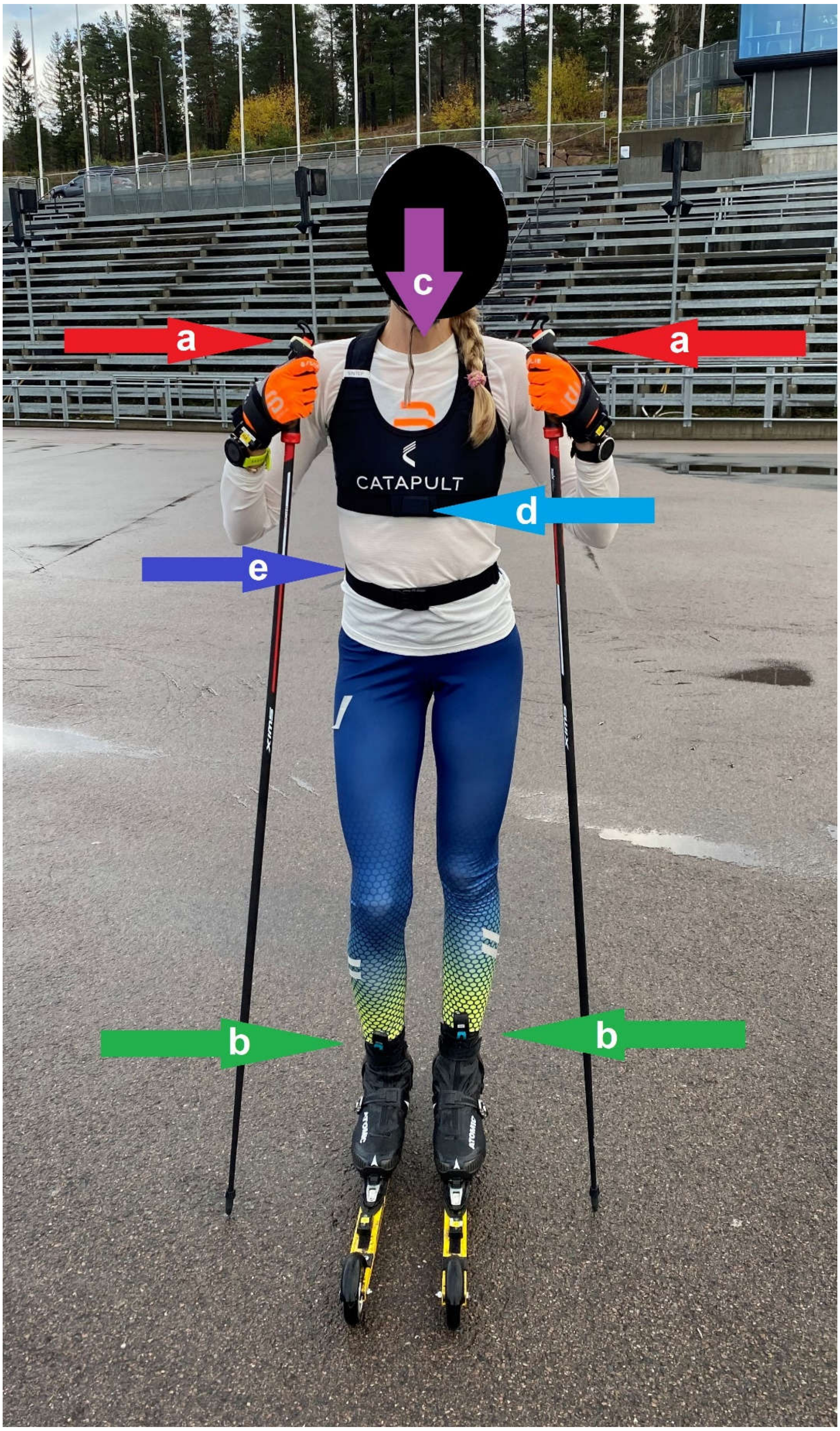


**Figure 2.** Experimental setup, showing the equipment, with the force poles indicated with red arrows (a), force insoles with green arrows (b), catapult sensor on the upper back (hidden) with a purple arrow (c), IMU on the sternum with a light blue arrow (d) and IMU on the sacrum (hidden) with a dark blue arrow (e).

## 3. Calculations

### 3.1. Reference system

Data from each trial were processed using a dedicated Matlab procedure (Matlab R2019a, The MathWorks Inc., Natick, Massachusetts, USA). Skiing cycles were defined previously, starting when the left ski hit the ground [21]. The reference values for $P_{ON}$ and $P_{OFF}$ were obtained by the force poles, using a threshold of 5% of bodyweight. The force insoles were used to determine $S_{ON}$ and $S_{OFF}$ for each ski, with a threshold of 7% of bodyweight [22]. The temporal events were then turned into three sequential series. For the poles, the timeseries was set as "1" between $P_{ON}$ and $P_{OFF}$ and set as "0" between $P_{OFF}$ and the next $P_{ON}$. The pole contact times are therefore represented as "1", while pole swing times are represented by "0". The same method was used for each foot, with ski contact time represented as "1" and ski swing time represented as "0" in two other time sequences.

### 3.2. Machine learning model

For the machine learning process, the three IMUs (one Optimeye S5 and two Physilog 5) were used individually to train one dedicated LSTM neural network for each time sequence (one pole and two skis). The features used for machine learning consisted in the three-dimensional accelerometer and gyroscope data from the selected sensor. As the Physilog 5 sensors recorded at 512 Hz, a down-sampling to 100 Hz was applied. The structure of the LSTM network consisted of a sequence input layer with six features, an LSTM layer with 200 hidden units, a fully connected layer for two classes, a softmax layer and a classification layer. The hidden units were chosen with empirical tests, starting with a limited number of units and increasing the number progressively, until the performance of the system stops improving for the first trained network.

A leave-one-out method was used to train the networks and perform the analysis, with each subject being removed from the training set and used as test set. Each network was trained on 100 epochs.

Once trained, the output sequences were filtered to combine adjacent blocks (e.g., sequences of "1") separated by less than 20 samples (0.2 s), and only keep blocks that are longer than 30 samples (0.3 s).

### 3.3. Analysis

For each subject, the time difference between the reference and the LSTM output obtained on the remaining subjects was computed for each event. The contact time (CT) and flight time (FT) were also computed and compared, both in absolute and relative terms. For each parameter, the mean error and standard deviation (sd) were calculated over all trials of each participant. The results were then combined to determine the overall accuracy (mean of the means) and precision (mean of the sd's). The number of events missed, as well as the number of additional events detected by the ML are also presented.

## 4. Results

With the leave-one-out method, a total of 81 LSTM network were trained (e.g., nine participants times three IMUs time three parameters). For the determination of the $P_{ON}$, the IMU placed on the upper back provided the best outcome. It reached an accuracy and precision of -2 ± 40 ms with a high number of events correctly assessed (5.0% of the events missed and 3.7% found in extra) (Table 1). The results obtained with the IMU placed on the sacrum provided the poorest outcome with a lot of errors in the events determination (38.0% of the events missed and 21.0% found in extra). For the $P_{OFF}$, the IMU placed on the upper back also provided the best results, with an accuracy and precision of 8 ± 54 ms and the highest number of events correctly assessed (5.6% events missed and 4.2% extra). Again, the lowest accuracy was obtained by the IMU placed on the sacrum.

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**Table 1.** Results for the parameters obtained for the poles, using the sensor placed on the sacrum (A), the sternum (B) and the upper back (C). Each line represents the training of the network on eight participants, tested on the remaining one.

| **A** | REF cycles | ML cycles | PON error (ms) mean ± sd | missed IC (%) | extra IC (%) | POFF error (ms) mean ± sd | missed TC (%) | extra TC (%) | CT error (ms) mean ± sd | FT error (ms) mean ± sd |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ1 | 1120 | 1157 | 29 ± 40 | 3 | 6 | 78 ± 73 | 9 | 12 | 57 ± 84 | -59 ± 87 |
| SJ2 | 1080 | 1079 | 30 ± 57 | 6 | 6 | -41 ± 93 | 10 | 10 | -69 ± 114 | 65 ± 110 |
| SJ3 | 1063 | 762 | 30 ± 60 | 31 | 4 | 39 ± 67 | 31 | 4 | 12 ± 75 | -10 ± 71 |
| SJ4 | 1043 | 734 | -85 ± 63 | 35 | 7 | -47 ± 83 | 34 | 6 | 23 ± 77 | -26 ± 78 |
| SJ5 | 1108 | 851 | -50 ± 71 | 39 | 20 | 7 ± 113 | 40 | 21 | 35 ± 103 | -44 ± 100 |
| SJ6 | 1760 | 1120 | 95 ± 153 | 79 | 67 | 155 ± 129 | 71 | 54 | 7 ± 81 | -11 ± 69 |
| SJ7 | 1095 | 597 | -27 ± 70 | 46 | 2 | 42 ± 92 | 49 | 6 | 53 ± 91 | -46 ± 92 |
| SJ8 | 1265 | 1203 | 6 ± 70 | 15 | 11 | -43 ± 96 | 15 | 10 | -39 ± 115 | 45 ± 116 |
| SJ9 | 987 | 317 | 121 ± 162 | 89 | 67 | 130 ± 163 | 89 | 66 | 4 ± 59 | 0 ± 16 |
| mean | 1169 | 869 | 17 ± 83 | 38.0 | 21.0 | 36 ± 101 | 38.5 | 20.9 | 9 ± 89 | -10 ± 82 |
| sd | 234 | 298 | 66 ± 43 | 29.9 | 26.5 | 75 ± 30 | 27.4 | 22.8 | 41 ± 19 | 42 ± 30 |
| total | 10521 | 7820 | | | | | | | | |

| **B** | REF cycles | ML cycles | PON error (ms) mean ± sd | missed IC (%) | extra IC (%) | POFF error (ms) mean ± sd | missed TC (%) | extra TC (%) | CT error (ms) mean ± sd | FT error (ms) mean ± sd |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ1 | 1120 | 1108 | 6 ± 43 | 8 | 7 | 59 ± 69 | 8 | 7 | 58 ± 84 | -59 ± 85 |
| SJ2 | 1080 | 1044 | 25 ± 32 | 7 | 4 | 46 ± 90 | 8 | 5 | 21 ± 99 | -24 ± 98 |
| SJ3 | 1063 | 1101 | 13 ± 45 | 4 | 8 | -35 ± 66 | 7 | 10 | -43 ± 77 | 42 ± 78 |
| SJ4 | 1043 | 1003 | -24 ± 31 | 21 | 18 | 17 ± 64 | 21 | 18 | 34 ± 68 | -36 ± 67 |
| SJ5 | 1108 | 1212 | 1 ± 60 | 8 | 16 | 35 ± 113 | 14 | 22 | 22 ± 119 | -32 ± 122 |
| SJ6 | 1760 | 1498 | -51 ± 39 | 18 | 4 | 18 ± 65 | 20 | 6 | 58 ± 76 | -56 ± 76 |
| SJ7 | 1095 | 1106 | 12 ± 59 | 11 | 12 | -14 ± 91 | 11 | 12 | -25 ± 82 | 29 ± 76 |
| SJ8 | 1265 | 1205 | 7 ± 55 | 11 | 7 | -32 ± 76 | 12 | 8 | -35 ± 83 | 39 ± 81 |
| SJ9 | 987 | 877 | -5 ± 78 | 39 | 32 | 43 ± 116 | 42 | 35 | 53 ± 89 | -51 ± 91 |
| mean | 1169 | 1128 | -2 ± 49 | 13.9 | 11.7 | 15 ± 83 | 15.8 | 13.5 | 16 ± 86 | -16 ± 86 |
| sd | 234 | 172 | 23 ± 15 | 10.7 | 9.0 | 35 ± 20 | 11.0 | 9.8 | 40 ± 15 | 42 ± 16 |
| total | 10521 | 10154 | | | | | | | | |

| **C** | REF cycles | ML cycles | PON error (ms) mean ± sd | missed IC (%) | extra IC (%) | POFF error (ms) mean ± sd | missed TC (%) | extra TC (%) | CT error (ms) mean ± sd | FT error (ms) mean ± sd |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ1 | 1120 | 1156 | 56 ± 29 | 1 | 4 | 63 ± 52 | 1 | 4 | 13 ± 66 | -14 ± 66 |
| SJ2 | 1080 | 1104 | 90 ± 30 | 2 | 4 | 69 ± 68 | 3 | 5 | -20 ± 76 | 19 ± 78 |
| SJ3 | 1063 | 1056 | -18 ± 42 | 7 | 6 | -32 ± 40 | 7 | 6 | -14 ± 63 | 11 ± 60 |
| SJ4 | 1043 | 984 | -61 ± 32 | 8 | 2 | -28 ± 52 | 8 | 2 | 29 ± 58 | -31 ± 60 |
| SJ5 | 1108 | 1127 | -40 ± 60 | 2 | 3 | 3 ± 45 | 2 | 4 | 38 ± 85 | -38 ± 89 |
| SJ6 | 1760 | 1572 | -5 ± 31 | 13 | 3 | 36 ± 44 | 16 | 6 | 36 ± 54 | -35 ± 54 |
| SJ7 | 1095 | 1042 | -36 ± 36 | 6 | 1 | -17 ± 45 | 6 | 1 | 20 ± 59 | -19 ± 58 |
| SJ8 | 1265 | 1292 | 18 ± 51 | 2 | 5 | -5 ± 68 | 3 | 5 | -24 ± 63 | 24 ± 63 |
| SJ9 | 987 | 977 | -26 ± 45 | 6 | 5 | -15 ± 76 | 6 | 5 | 9 ± 83 | -9 ± 84 |
| mean | 1169 | 1146 | -2 ± 40 | 5.0 | 3.7 | 8 ± 54 | 5.6 | 4.2 | 10 ± 67 | -10 ± 68 |
| sd | 234 | 187 | 49 ± 11 | 3.9 | 1.5 | 38 ± 13 | 4.6 | 1.7 | 24 ± 11 | 23 ± 13 |
| total | 10521 | 10310 | | | | | | | | |

REF is the reference method to determine the events and ML is the machine learning method. PON is the event when the pole hit the ground, POFF is the event when the pole leaves the ground. CT is the contact time and FT is the flight time. SJ# is the subject analysed in the leave one out method.

Concerning the determination of events of the skis, the IMU placed on the sternum and upper back provided relatively similar results, with a slightly better overall outcome for the IMU placed on the upper back. It reached an accuracy and precision of 1 ± 61 ms for SON with a number of missed events of 12.5% and a number of events detected in extra of 14.2%. For the SOFF, the accuracy was 0 ± 53 ms, 11.8% of the events were missed and

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14.3% of the events were found in extra (Table 2). The IMU on the sacrum provided the lowest accuracy for the events related to the poles.

When analysing the inner-cycle phases of the poles, the IMU placed on the upper back provided the best accuracy and precision for the CT (10 ± 67 ms), while the IMU placed on the sacrum and on the sternum provided a poorer precision (Table 1). The accuracy and precision of the poles FT gave a similar outcome, with the IMU placed on the upper back providing the best outcome (-10 ± 68 ms). Compared to the average length of the inner-cycle phase length, a relative pole CT error of 15.8% and a relative pole FT of 10.4% were obtained.

For the inner-cycle phases of the skis, the IMU placed on the upper back also provided the best precision, with (0 ± 63 ms) for the CT and (1 ± 65 ms) for the FT. The precision for the IMU placed on the sacrum and on the sternum provided almost the same precision (Table 2). For the skis, the relative error was 7.6% for the CT and 11.2% for the FT.

**Table 2.** Results for the parameters obtained for the skis, using the sensor placed on the sacrum (**A**), the sternum (**B**) and the upper back (**C**). Each line represents the training of the network on eight participants, tested on the remaining one.

| **A** | REF cycles | ML cycles | PON error (ms) mean ± sd | missed IC (%) | extra IC (%) | POFF error (ms) mean ± sd | missed TC (%) | extra TC (%) | CT error (ms) mean ± sd | FT error (ms) mean ± sd |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ1 | 1120 | 1157 | 52 ± 65 | 10 | 5 | -9 ± 56 | 10 | 4 | -56 ± 74 | 54 ± 75 |
| SJ2 | 1080 | 1079 | -66 ± 60 | 13 | 7 | -62 ± 60 | 15 | 9 | 1 ± 82 | 0 ± 81 |
| SJ3 | 1063 | 762 | 29 ± 72 | 16 | 7 | 13 ± 45 | 15 | 6 | -14 ± 77 | 16 ± 78 |
| SJ4 | 1043 | 734 | -24 ± 62 | 6 | 3 | -14 ± 35 | 5 | 3 | 9 ± 64 | -10 ± 65 |
| SJ5 | 1108 | 851 | -13 ± 92 | 29 | 18 | -44 ± 78 | 29 | 17 | -14 ± 82 | 18 ± 91 |
| SJ6 | 1760 | 1120 | 62 ± 152 | 95 | 94 | -60 ± 165 | 96 | 95 | 1 ± 10 | 1 ± 23 |
| SJ7 | 1095 | 597 | 53 ± 94 | 20 | 13 | 7 ± 53 | 15 | 8 | -33 ± 93 | 38 ± 96 |
| SJ8 | 1265 | 1203 | 10 ± 72 | 7 | 7 | 55 ± 47 | 5 | 5 | 42 ± 88 | -40 ± 90 |
| SJ9 | 987 | 317 | -32 ± 167 | 88 | 81 | -27 ± 145 | 91 | 86 | 3 ± 30 | 5 ± 56 |
| mean | 1169 | 869 | 8 ± 93 | 31.5 | 26.0 | -16 ± 76 | 31.2 | 25.8 | -7 ± 66 | 9 ± 73 |
| sd | 234 | 298 | 44 ± 40 | 34.8 | 35.1 | 37 ± 47 | 36.1 | 36.8 | 27 ± 28 | 27 ± 23 |
| total | 10521 | 7820 | | | | | | | | |

| **B** | REF cycles | ML cycles | PON error (ms) mean ± sd | missed IC (%) | extra IC (%) | POFF error (ms) mean ± sd | missed TC (%) | extra TC (%) | CT error (ms) mean ± sd | FT error (ms) mean ± sd |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ1 | 1120 | 1108 | 41 ± 68 | 18 | 7 | 6 ± 46 | 17 | 6 | -27 ± 67 | 28 ± 72 |
| SJ2 | 1080 | 1044 | -1 ± 88 | 12 | 6 | -43 ± 52 | 11 | 4 | -33 ± 89 | 32 ± 88 |
| SJ3 | 1063 | 1101 | -5 ± 66 | 13 | 5 | 12 ± 36 | 13 | 5 | 15 ± 73 | -15 ± 74 |
| SJ4 | 1043 | 1003 | 20 ± 58 | 6 | 25 | 13 ± 40 | 5 | 25 | -5 ± 69 | 4 ± 72 |
| SJ5 | 1108 | 1212 | -19 ± 77 | 22 | 16 | -38 ± 69 | 22 | 16 | -11 ± 75 | 15 ± 80 |
| SJ6 | 1760 | 1498 | -22 ± 47 | 8 | 4 | -18 ± 47 | 7 | 4 | 4 ± 56 | -3 ± 57 |
| SJ7 | 1095 | 1106 | 26 ± 82 | 18 | 17 | 13 ± 70 | 16 | 15 | -11 ± 65 | 12 ± 70 |
| SJ8 | 1265 | 1205 | -1 ± 57 | 4 | 4 | 28 ± 39 | 4 | 4 | 28 ± 61 | -27 ± 64 |
| SJ9 | 987 | 877 | 8 ± 103 | 28 | 39 | 4 ± 82 | 26 | 38 | -13 ± 78 | 8 ± 81 |
| mean | 1169 | 1128 | 5 ± 72 | 14.2 | 13.8 | -3 ± 53 | 13.5 | 13.1 | -6 ± 70 | 6 ± 73 |
| sd | 234 | 172 | 21 ± 18 | 7.9 | 12.1 | 24 ± 16 | 7.6 | 11.9 | 19 ± 10 | 19 ± 9 |
| total | 10521 | 10154 | | | | | | | | |

| **C** | REF cycles | ML cycles | PON error (ms) mean ± sd | missed IC (%) | extra IC (%) | POFF error (ms) mean ± sd | missed TC (%) | extra TC (%) | CT error (ms) mean ± sd | FT error (ms) mean ± sd |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ1 | 1120 | 1156 | 67 ± 53 | 15 | 10 | 24 ± 39 | 12 | 7 | -37 ± 60 | 40 ± 63 |
| SJ2 | 1080 | 1104 | 38 ± 64 | 11 | 6 | 39 ± 44 | 9 | 4 | 3 ± 72 | -2 ± 77 |
| SJ3 | 1063 | 1056 | -24 ± 57 | 14 | 6 | -23 ± 46 | 14 | 5 | 4 ± 66 | -3 ± 68 |

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| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| SJ4 | 1043 | 984 | -35 ± 51 | 6 | 27 | -32 ± 46 | 5 | 27 | 7 ± 69 | -5 ± 69 |
| SJ5 | 1108 | 1127 | -47 ± 63 | 12 | 17 | -44 ± 61 | 12 | 17 | 2 ± 61 | -2 ± 66 |
| SJ6 | 1760 | 1572 | -5 ± 50 | 6 | 4 | 13 ± 49 | 6 | 4 | 18 ± 57 | -17 ± 59 |
| SJ7 | 1095 | 1042 | 0 ± 78 | 21 | 18 | -14 ± 74 | 19 | 16 | -13 ± 65 | 16 ± 67 |
| SJ8 | 1265 | 1292 | 17 ± 47 | 4 | 5 | 35 ± 40 | 4 | 4 | 18 ± 48 | -17 ± 52 |
| SJ9 | 987 | 977 | 3 ± 84 | 25 | 36 | 0 ± 83 | 25 | 36 | -1 ± 67 | -5 ± 68 |
| mean | 1169 | 1146 | 1 ± 61 | 12.5 | 14.2 | 0 ± 53 | 11.8 | 13.4 | 0 ± 63 | 1 ± 65 |
| sd | 234 | 187 | 36 ± 13 | 7.0 | 11.3 | 30 ± 16 | 6.9 | 11.6 | 17 ± 7 | 17 ± 7 |
| total | 10521 | 10310 | | | | | | | | |

REF is the reference method to determine the events and ML is the machine learning method. SON is the event when the pole hit the ground, SOFF is the event when the pole leaves the ground. CT is the contact time and FT is the flight time. SJ# is the subject analysed in the leave-one-out method.

## 5. Discussion

The current study determined temporal events in roller ski skating by employing a time-sequential information-based deep Long Short-Term Memory (LSTM) neural network from a single IMU. To the best of our knowledge, it is the first time that a machine learning method is used on a single IMU to determine temporal events and inner-cycle parameters of human motion. The best model, using an IMU placed on the upper-back, predicted events with a 49 to 55 ms accuracy. The resulting inner-cycle phases were then estimated with a precision between 63 and 68 ms. For the poles, around 5.5% of the events were missed and around 4% of extra events were found. For the skis, around 12% of the events were missed and around 14% of extra events were found.

The accuracy of the events determination is lower than a previously published work using four IMUs placed on the wrists and skis [20]. In that study an accuracy between 7 to 26 ms was obtained to determine the events, and the inner-cycle parameters provided a precision between 49 and 58 ms. This would be enough, for example, to distinguish skis' CT between low vs high intensity (e.g., 100 ms differences) but not for the poles CT (e.g., 50 ms differences)[23]. . When compared to the inner-cycle phases durations, the relative precision of 7.6% obtained for the skis' CT is half of the 15.8% obtained for the poles' CT. The athletes are indeed spending much less time pushing on the poles than gliding on the skis during the cycle. For the FT, the skis and the poles obtained similar precision (11.2% and 10.4% respectively). Aggregating several cycles over a track portion could help providing a more robust outcome. Indeed, the SD of the accuracy reached 24 ms for the poles' inner-cycles parameters and 17 ms for the skis, showing potential improvement for averaging multiples cycles. The precision of the method could probably be further improved by using a reference system with a higher acquisition frequency [22]. The manual synchronization between the IMUs and the reference systems could also be improved and the clock jitter between the sensors could be corrected to provide better input to the LSTM network. Indeed, if the accuracy of the synchronisation is not a major concern when determining the inner-cycles parameters in a traditional approach, this could lead to noisy inputs to train the network in a ML approach. The need to filter data once the classification is achieved could also influence the accuracy. Finding a method to avoid the filtering step could slightly improve the overall accuracy and the simplify the analysis.

Another element that could have influenced the accuracy of the method is how well the IMUs were fixed to the body. We observed that the IMUs placed on the upper back and on the chest, in the dedicated vest were more stable compared to the IMU placed on the sacrum using a belt. This could explain the difference between IMU placement, as we expected to have better results for the legs with the sensor on the sacrum.

Approximately 95% of the poles' events were detected here, when 97% were correctly assessed using a four IMUs configuration [20] and 99% were correctly assessed in the lab [19]. These numbers are coherent as we expect field conditions to be more challenging. The 86-88% accuracy for the skis' events compared to 97% obtained with the four IMUs configuration can be explain by the fact that each cycle is included in the present work, while only the G2 to G5 cycles were included in the previous work [20]. For G5 in particular, the accuracy was also lower than 90%. Concerning the higher number of events missed and events found in extra for the skis compared to the poles, the higher variability of the skis' cycles could be an explanation. Indeed, skis can have a very long CT in strait downhill or very short succession of CT and FT in downhill turns, where it is difficult to assess if the ski is in contact with the ground or not.

Several trained LSTM networks provided bad outcome for some participants. The high disparity between participants' level and technique and the low number of participants could be the cause for several bad accuracy for some of the trained LSTM network. Including more participants could resolve this issue and improve the robustness of the method, even if a total of 10'000 poles cycles and almost 18'000 ski cycles were detected. This would also allow to compare different network architectures and methods, to provide an optimized solution. With the current dataset, an extensive optimisation could lead to an overfitted solution.

## 6. Conclusions

This work describes the development of the first machine learning method able to assess temporal events and inner-cycle phases from a single deported IMU in human locomotion. The method is able to detect 95% of the temporal events of the poles, 87% of the skis, and provide a precision of around 60 ms for the different inner-cycle phases. This precision would allow an overall view of an athlete's technique in the field, but not to compare technical changes lower than 10%. Overall, the proposed LSTM method provides a promising tool for assessing temporal events and inner-cycle phases in roller ski skating, showing the potential of using a deported IMU to estimate different spatio-temporal parameters of human locomotion.

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**Ethics Declaration:** The study was carried out in accordance with the institutional requirements and in line with the Helsinki Declaration.

**Institutional Review Board Statement:** The Regional Committee for Medical and Health Research Ethics waives the requirement for ethical approval for such study.

Approval for data security and handling was obtained from the Norwegian Center for Research Data before commencement of the study.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

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