Motion Estimation Using Inertial Sensor Technology with Applications to Sporting Exercises

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ABSTRACT

The ability to measure performance related indicators in training and competitive environments is important for coaches in a number of sports. The testing and monitoring of athletes outside of the laboaratory is a comparatively new field that has been facilitated by advancements in micro-electromechanical systems technology. The aim of this study was to test the efficacy of systems using micro accelerometers to measure foot-ground contact time, a key parameter in running performance, and quickly provide feedback. Experiments were conducted to a) compare results of single steps from jogging and running using different types of devices and b) compare results for several sprint strides from four individuals. The results show that accurate measurement of ground contact time is possible outside of a laboratory with inertial sensors and the developed algorithm. With the use of a smartphone or tablet to control the sensors and visualise the results, the high precision, low cost, minimal size and ease of the tested system makes it perfect for use by elite coaches and recreational athletes.

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Introduction

It is becoming increasingly important for coaches to track the displacement or specific motion profiles of various exercises performed by their athletes. This permits them to make quantitative analyses that could help to enhance the efficiency of the exercises or prevent injuries. Traditionally, the measurement of athletic performance is done mostly in a laboratory environment[1], where the specific testing of physiological indicators can take place. Laboratory testing, however, places limits on how the athlete performs, as the conditions differ from the training environment. In addition, performance characteristics are further augmented during competition compared to training. By better understanding their athletes' performances during training and competition, coaches can work more effectively with them to improve performance[2].

A number of factors and trade-offs need to be considered when testing athletes outside of the laboratory environment. These include the test or measurement desired, the technologies that can be used, the practicality of obtaining measurements, and specific considerations related to the sport. For example, in the case of sprinting, one consideration would be the weight of a measurement apparatus worn by the athlete: if it is too heavy it may disturb the running movement. Thus, size, weight, and power are very important factors when considering sport specific systems. The testing and monitoring of athletes in their natural training environment is a comparatively new field that has been facilitated by the advancements in the field of micro-electromechanical systems (MEMS) technology[2].

Inertial measurement units (IMUs), which consist of a three-axis accelerometer, a three-axis gyroscope and a three-axis magnetometer, have been used as a sensing unit for motion determination as they can measure acceleration, rotation angles and magnetic field[3]. However, these miniaturised inertial systems have limited capabilities for calculating orientation and displacement. The main problem is that displacement is computed by time integrating the signals from gyros and accelerometers, which includes any superimposed sensor drift and noise. Therefore, the estimation errors tend to grow indefinitely. Solutions for mitigating the drift problem usually consist of combining data from additional sensors such as magnetometers[4] , or the incorporation of problem-specific knowledge, for example gait cycle, which assists with error correction[5]. Despite this, IMUs make it possible to fulfil the various handiness requirements mentioned above and provide a preferable option for this application[3,6].

During walking and running, body segments go through a cyclic motion and the movement pattern of each segment is repeated in every stride cycle. The term 'gait' is used to describe the way of walking or running[7]. As shown in Figure 1, during each gait cycle a sequence of events takes place, marking the transition from one phase to another. When walking, each gait cycle begins and ends with the heel strike. With

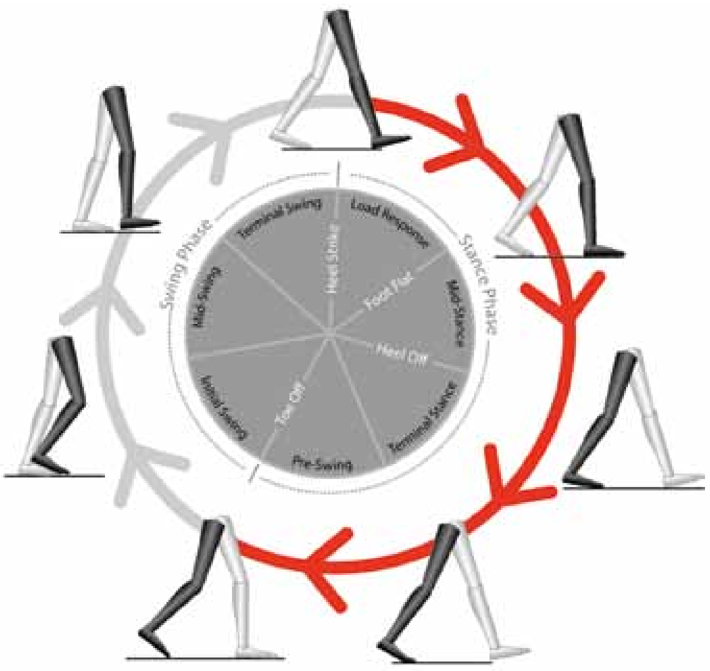


Figure 1: Different gait phases during walking (after Whittle[8])

running, the landing is further forward on the foot (referred to as midfoot strike) and a pronounced forefoot landing as the velocity increases. This cyclic motion of a body segment generates a periodic acceleration, which can be detected by inertial sensors. The embedded features in IMUs enable the possibility of estimating different parameters in order to analyse the running performance[9].

Foot-ground contact time, shown as the red arrow in Figure 1, is one of the most important variables influencing running velocity, with better sprint athletes exhibiting shorter contact times[10]. This variable is also affected by leg stiffness, with a higher stiffness associated with reduced contact times[11]. Sprint training aims to reduce contact times by focusing on the development of explosive force during the stretch-shorten cycle of muscular contractions, designed to enhance leg stiffness. Therefore, from a coaching perspective, measuring the contact time during sprinting would be very beneficial providing information that could be used to monitor performance, as well as evaluating the effect of the training on the technique.

PARTwear (HuCE-microLab, Biel/Bienne, Switzerland) is an accelerometer used to monitor the activity of individuals. At the request of a coaching colleague, we conducted an analysis of running performance through the gait cycle using the PARTwear system. The aims were to test the efficacy of the system and obtain objective feedback and findings that could be applied to other track and field athletes as well as to performers in others sports.

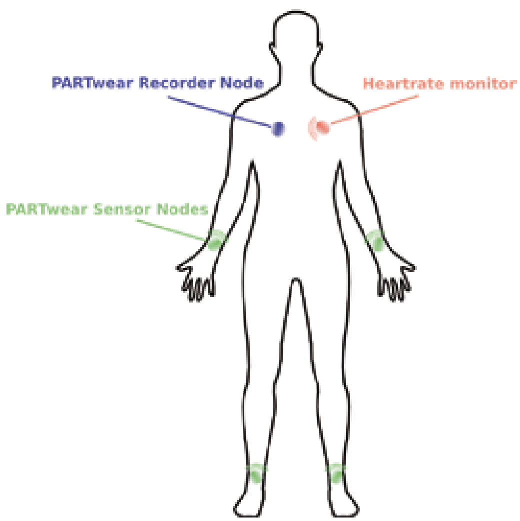
Methods

Algorithm design

Experiments were carried out on a treadmill and an outdoor 50m track, with the acceleration data recorded by the PARTwear. The purpose was to analyse the acceleration signal associated with the foot-ground contact time during jogging and sprinting in order to calculate and develop an algorithm to incorporate with the PARTwear system. The data was collected in real-time and processed using Matlab/Simulink® from Mathworks [12].

Description of PARTwear-Sensor-System

In its most simple setup, raw data is recorded onto the internal flash memory card of the



Measurement of acceleration in the range of +/- 16 g at up to 3200Hz sampling rate

Measurement of heart rate via ANT[13] wireless connection

Wireless sensor network for synchronous recording of multiple sensor nodes

Easily adaptable online signal processing

Up to 14 days of autonomous operation from single battery

Small, robust and biomechanically neutral to the athlete due to flexible silicone casing

Figure 2: PARTwear - Performance Analysis Research Technology

Figure 3: PARTwear unfolded without casing (left), with silicone casing (center) and folded (right)

PARTwear device. It is possible to have the data processed online, however, only certain features of will be recorded. In addition, heart rate (HR) can be recorded with use of a wireless HR belt. What separates the PARTwear system from its competitors, is its ability to synchronously record data from multiple devices, over a wireless connection, to a recording node. Furthermore, it is designed to easily integrate algorithms based on the physical requirements of the athlete.

The PARTwear system can be configured to play different roles, with the most basic being the **Stand-alone**, where data from both the accelerometer and HR belt (optional) can be processed and recorded. In the Recorder role, collection from other sensor nodes are carried out, processed and recorded. When the recorder node is plugged to a host computer via USB, a live stream recording of the data can be sent for real time analysis. The sensor platform consists of two rigid circuit boards connected by a flexible part allowing it to be shaped into any form or around any structure (Figure 3). The standard thin flexible battery encased in silicone, can be mounted below or beside the PCB (printed circuit board), with custom casings and integrations (e.g. protectors) being possible.

Measurement

With the PARTwear worn on the participant's right foot, measurements were taken (Figure 4). Three dimensional acceleration data was recorded with use of a MEMS based sensor (ADXL345; Analog Devices) and sampled by a Texas Insturments 16-bit microprocessor (MSP430) at 2000 Hz per channel. With the use of a forrfoot strike platter, the participant ran on a treadmill then on a 50m track. Each run was filmed with a GoPro HERO3® camera (Figure 4) at 240 frames per second. This enabled the comparison of the measured accelerations to the realtime movement of the individual's right foot. In order to synchronise the recorded video with the acceleration data, a sync pattern was generated at the beginning of each run by having the red LED on the PARTwear device blink three times. Additionally, this LED state was stored on the internal memory of the device (Figure 5).

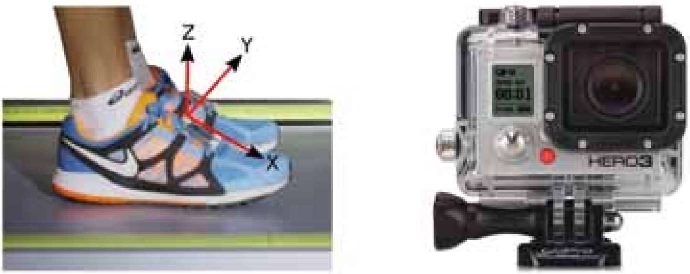


Figure 4: PARTwear sensor attached to the right foot (Positive directions of the three acceleration axes are superimposed. (left), and GoPro HERO3® camera (right))

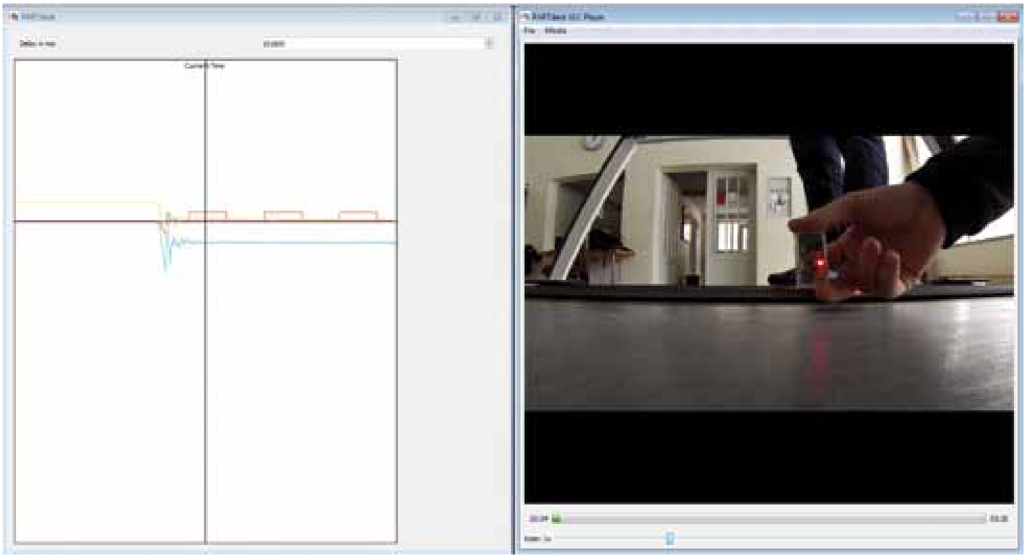


Figure 5: The red LED on the PARTwear sensor platform is generating a sync pattern

Algorithm Evalutaion

The generated algorithm was evaluated with the MATLAB/ SIMULINK® [12] program by Mathworks. By measuring the distance between the peaks in the signal (maxima and minima above a certain threshold), the contact time between the foot and the ground was calculated (Figure 6). In turn, a number of criteria were developed and tested in order to determine contact time. The first part of the algorithm observed the positive and negative peaks in the repetitive acceleration pattern of the z axis (red and black dots Figure 6). This referred to both the minima in the Z acceleration axis near the beginning of ground contact and the toe-off phase, respectively. The use of video analysis also made it possible to calculate the contact time, indicated by the blue line in Figure 6.

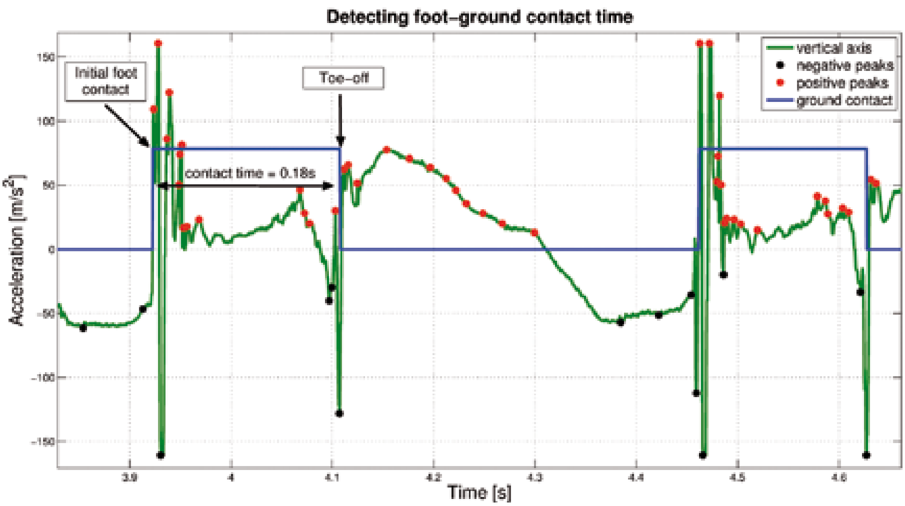


Figure 6: Detecting foot-ground contact time using a peak detection algorithm

Figure 7: Acceleration data of each sensor axis and the computed foot-ground contact time as well as the step rate are displayed in a video file

Visualisation

Using MATLAB'S COMPUTER SYSTEM VISION TOOLBOX®, the raw data, the computed ground contact times and the step rate for each run was visualised. The contact time for each step and step rate is displayed by a blue and orange bar, respectivley (Figure 7). At the bottom of the video, the raw data of the three acceleration sensor axes were synchronously plotted to the video image. It was concluded from this visualisation that close estimates of foot-ground contact time during running can be obtained using body mounted accelerometers, with the best estimates associated with the highest accelerations. At the beginning of a run, computing the foot-ground contact time was not possible since the acceleration peaks were not significant, and therefore, were not observed by the algorithm.

Experiment A

In order to determine the accuracy of the estimated ground contact time by the algorithm, a comparison between two measuring devices was conducted. The first device was a force plate (KISTLER; 0.90 x 0.90m Quattro Jump,

Figure 8: Red high-speed camera (left) and measurement setup with Kistler force plate and Optojump (right)

Winterthur, Switzerland. 500Hz sampling rate), and the second was an Optojump (Next Microgate, Bolzano, Italy. 1000Hz sampling rate), an optical measuring device consisting of a transmitting and receiving bar. As a reference point, a Red high-speed camera (Epic Mysterium-X, Red Digital Cinema Camera Company, Lake Forest, California), was used to record video data at 350Hz in full HD (1920 x 1080) resolution (Figure 8).

The participant in this experiment was an experienced mid to forefoot runner, and a former top triathlete (25.8y, 182cm, 67kg). The set-up for the experiment allowed the measurement of a step. The athlete was asked to run along a predefined 50m runway, with a sample being recorded when maximum running speed was reached. In total, four test runs were conducted while jogging and sprinting, with the results being compared to the video data from the high-speed camera. Concerning the set-up of the force plate, two measuring limits (5N and 10N) were selected, in order to avoid the influence of artefacts due to ground vibrations.

Experiment B

The second experiment measured the ground contact time when sprinting along a 10m runway. Unlike experiment A, which compared one step to several measuring systems, the aim was to measure the contact time of every step using the OPTOJUMP system. Four participants, two elite sprinters and two recreational runners, were involved. In turn, this enabled the evaluation of inter-subject variability.

Results

Experiment A

The results from experiment A are shown in Figure 9. The image on the left represents the ground contact times of the four measured steps when jogging, and on the right, when sprinting. Statistical analysis was used to compare each measurement against the reference signal from the high-speed camera. When jogging, the ground contact times of the RED ranged between a minimum of 177 ms and maximum of 191 ms, compared to a minimum of 137 ms with a maximum of 160 ms for sprinting. The mean for the absolute and maximum error of each measuring device was calculated and summarised in Tables 1 and 2. When jogging, differences between the measuring devices for an absolute error ranged between 0.9% and 4.0%, with a maximum of 2.3% and 6.2%. With regard to sprinting, these differences were between 1.5% and 3.5% for the absolute and 2.1% and 6.6% for the maximum error, respectivley.

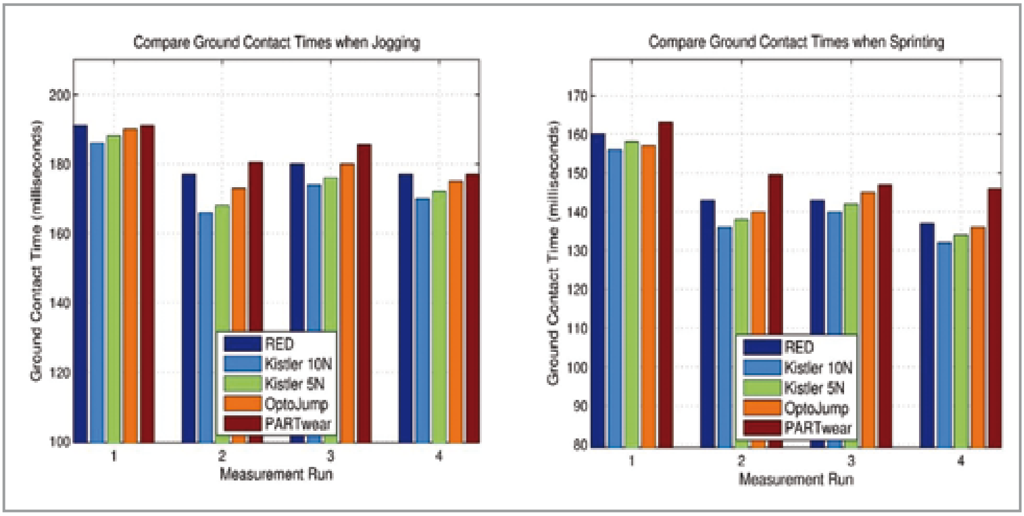


Figure 9: Compare ground contact times when jogging (left) and sprinting (right)

Table 1: Comparing different measuring devices for ground contact time when jogging against RED

Measuring Device	Mean Abs Error [%]	Max Error [%]
Kistler 10N	4.03	6.215
Kistler 5N	2.926	5.085
OptoJump	0.9783	2.26
PARTwear	1.258	3.056

Table 2: Comparing different measuring devices for ground contact time when sprinting against RED

Measuring Device	Mean Abs Error [%]	Max Error [%]
Kistler 10N	3.286	4.895
Kistler 5N	1.909	3.497
OptoJump	1.525	2.098
PARTwear	3.947	6.569

Experiment B

The results for experiment B are shown in Figure 10. The four images represent the ground contact times for each of the four participants. Statistical analysis compared each measurement against the reference signal from the Optojump. The ground contact times measured ranged between a minimum of 0.076 ms and a maximum of 0.203 ms. The mean for the absolute and maximum error of the designed algorithm for the ground contact time was calculated and presented in Table 3. The absolute error was between 2.6% and 7.0%, with the maximum error between 5.6% and 15.8%.

Table 3: Comparing ground contact times of four different persons against Optojump when sprinting

Test Person	Mean Abs Error [%]	Max Error [%]
1	6.973	14.85
2	5.365	15.79
3	2.629	5.556
4	3.453	8.163

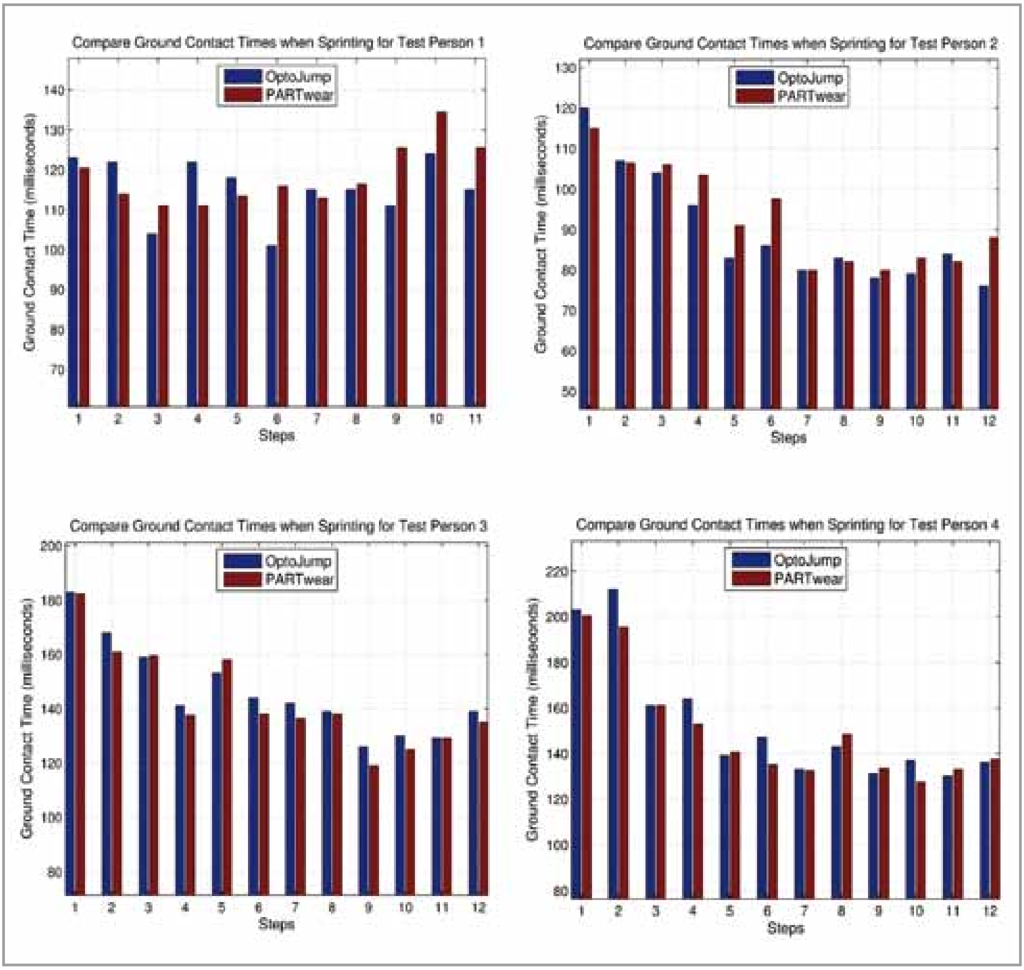


Figure 10: Comparing ground contact times of four different persons

Discussion

In the first experiment, the newly designed algorithm was compared against different measuring devices. The results indicated that the maximum error of the algorithm (3%) was similar to that of a laboratory device (2.2%) (i.e.,OPTOJUMP). Since the OPTOJUMP had the smallest error of all the measuring devices, it was used as a reference in the second experiment. The aim for this experiment was to analyse the inter-subject variability of the designed algorithm, when sprinting on a 10m track. Unlike experiment A, the contact time for each step was measured and observed.

Although the current study was based on a small sample size, the findings suggest that the algorithm can be applied to different individuals. In turn, the algorithm could be further improved with an adaption factor, found by using the cross-validation method. The C++ code of the current algorithm state was generated with the Embedded Coder from Matlab/ Simulink®, allowing the integration and testing of the algorithm on the embedded processors of the PARTwear sensor.

Conclusion

Since foot-ground contact time is one of the most important variables influencing maximum running velocity, it would be beneficial to measure it regularly during training. This results of this project show that the measurement of ground contact time is possible outside of a laboratory setting in the natural environment of the athlete with inertial sensors and the developed algorithm. With the use of a smartphone or tablet to control the sensors and visualise the results, the high precision, low cost, minimal size and ease of the PARTwear system makes it perfect for use by elite coaches and recreational athletes in track and field and other sports that involve running/sprinting.

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