A Wearable Device for Sport Performance Analysis and Monitoring

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***Abstract*—In this paper the use of a wearable device is considered in order to evaluate the performance of an athlete during her/his sport activities. The preliminary step consists of recording the motion variables at a sufficiently high sampling rate throughout the experimental campaign. The collected data are then elaborated by a PC-based application to identify the system dynamics and derive some synthetic performance indicators, by taking into account also the experience of the sport professionals. The extraction of the indicators is based on basic signal processing that can be implemented in algorithms run directly on the microcontroller unit (MCU) of the device. The key indicators values can be sent to other electronic devices by using one of the available wireless network connections at a reduced transmission rate. Some experimental data are also reported to illustrate the effectiveness of the approach.**

Keywords*—*wearable device; sport performance analysis; system identification; system synthetic indicators; experimental data.

I. INTRODUCTION

A wearable device can be defined as a small electronic equipment, able to collect data from some on-board sensors and perform simple elaborations on them in order to extract meaningful output data. These data can be sent wirelessly to other electronic devices for evaluation purposes. Their technology development is characterized by a rapid evolution thanks to new materials, more powerful and miniaturized microcontrollers (MCUs), more efficient and durable batteries. However, the innovation has been undoubtedly driven by advances in microelectromechanical systems (MEMS) realization. As of today, MEMS devices can contain triaxial accelerometers, triaxial gyroscopes, and pressure sensors in a very small size packages [1].

In the last years, the number of applications of wearable devices has grown exponentially [2]. They are employed for health monitoring [3], human-machine interaction [4], educational tools [5]. In particular, an important case study is represented by the sport activity monitoring and performance evaluation [2]. The study of the human motion is based on the variables which describe the kinematics and the dynamics of the anatomic segments, i.e. displacements, velocities and accelerations [6]-[8], which are fundamental for any accurate classification as required in the analysis of sport performance [9],[10]. The measurement of the dynamic characteristics of athletes is commonly done in a laboratory environment, where rigorous testing of biomechanics and physiology can take place [11]. However, some drawbacks have to be considered, e.g. the controlled environment is different to the natural training environment and expensive and hardly transportable measurement tools have to be employed [11].

Recently, the extremely small size of the sensors and the low power wireless communication technologies have led to the creation of portable devices that can be easily worn by the athletes during their training programs or even integrated into their sport equipment and clothes (see [1],[2] and the bibliography therein for some interesting examples). Indeed, the accelerometers in the wearable devices, if suitably positioned on different parts of a human body, allow analyzing different motion situations, such as standing and sitting postures, sit-stand transitions, trunk inclination variations, walking and running movement features [12],[13].

In this paper, it is discussed the application of a dedicated wearable device for the motion study of an athlete during a race. Admittedly, there are numerous systems available commercially, but, unfortunately, the majority of them implements relatively simple algorithms for computing fitness tracking metrics, which do not exploit sport specific knowledge [2],[11]. The selected system is based on a STMicroelectronics™ board, with storage capability via an SD card. The portable instrument consists of a 32-bit low power MCU, a tri-axis accelerometer, a tri-axis gyroscope, and a Bluetooth wireless transmission module, integrated with tri-axis magnetometer, barometric pressure and humidity sensors (see Fig. 1). The data are preliminarily collected in the SD-card, from the sensors available, at a predefined sample rate. They are then transferred to a PC, where more complex and sophisticated analyses are performed offline in the Matlab™ environment, in order to identify the system characteristics and derive synthetic indicators of the athlete's motion features. Such indicators are used to design algorithms for preprocessing data directly on the same device, compatible with the limited MCU computational resources, to obtain the most relevant information to send, so that a reduced transmission rate is needed, and the battery life is preserved. Some experimental data are also included to demonstrate the effectiveness of the proposed approach.

II. THE WEARABLE SYSTEM

The adopted wearable device is the STEVAL-STLCS01V1 by STMicroelectronics™. It is a comprehensive development kit for the SensorTile board illustrated in Fig. 1, which is provided with a cradle board (see Fig. 2). The SensorTile is a tiny, square-shaped (13.5 x 13.5 mm) IoT module equipped with a low power MCU and Bluetooth low energy connectivity as well as a complete set of motion and environmental MEMS sensors. The sensor data streaming is allowed via USB and logging on SD card, while sensor data transfer via Bluetooth Low Energy is also possible at lower sampling rate. Compared to other devices with the same characteristics, it has the advantages of being extremely small, portable and relatively cheap.

The main components of the board are summarized as follows:

- a 32-bit ultra-low-power MCU with Cortex®M4F;
- an iNEMO inertial module: 3D accelerometer and 3D gyroscope;
- an ultra-compact high performance eCompass module: ultralow power 3D accelerometer and 3D magnetometer;
- a MEMS nano-pressure sensor: 260-1260 hPa absolute digital output barometer;
- a BlueNRG-MS – Bluetooth low energy network processor.

The SensorTile board is used to record the main physical data of the athlete, for the activity monitoring of the system. The combination of the tri-axis accelerometer and the tri-axis gyroscope allows obtaining a complete MEMS IMU (iNEMO), with 6 degrees of freedom, for sensing the athlete's motion. The accelerometer measures linear acceleration with a full-scale acceleration range selectable within the set: {±2g, ±4g, ±8g, ±16g}. A FIFO memory of 4kB allows dynamic data batching (i.e. external sensors, timestamp, etc.) and the overall power saving of the system. An SPI interface is used for communication with the microcontroller.

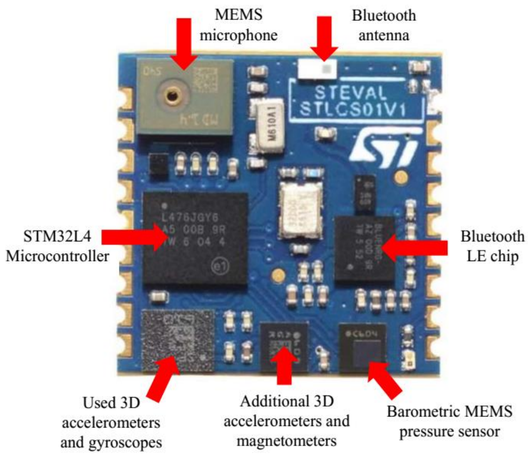

Fig. 1. SensorTile.

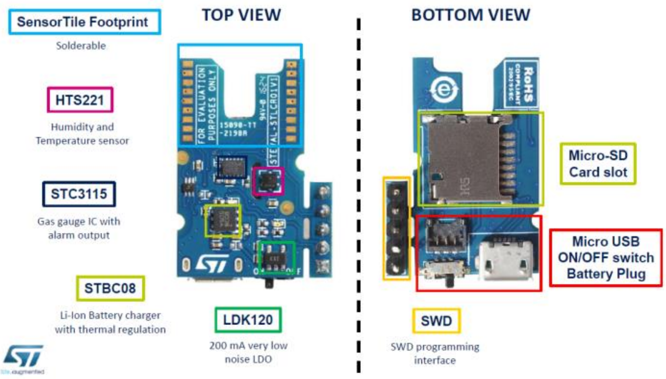

Fig. 2. SensorTile cradle board with SensorTile footprint.

III. THE GAIT CYCLE

The gait cycle represents the functional reference unit in the walking and running analysis. It is defined as the interval of time between two consecutive contacts of the same foot (stride) and represents the time reference for all the biomechanical events and muscle activity [14]. In Fig. 3 a schematic representation of the gait cycle is shown, where the main stance and swing phases are indicated. The first phase denotes the interval of time during which the foot is in contact with the ground; the second phase denotes the interval of time during which the leg is suspended and its forward progression is produced. A typical characteristic of walking is the period of time where both feet touch the ground (double support), which is normally lacking during running. The parameters related to both walking and running mechanics commonly considered by the sport specialists are: ground contact time, swing time (also known as flight time), stride length, and stride frequency/period [14].

Among the gait parameters, the contact time is of particular importance, as it is shown to be strictly related to the metabolic cost of locomotion, i.e. to the running economy [15]. Additionally, according to sport scientists, the reduction of ground contact time can produce a notable (positive) effect on race time and performance [15]. Accurate measurements of the ground contact time can be obtained by imbedding force plates beneath a treadmill belt. However, this solution is usually very expensive and not widely employed, also because the mechanics of running on a treadmill can differ from the one on the actual track. In [16], body-mounted accelerometer measurements are alternatively analyzed and shown to be sufficiently in accordance with laboratory force platform results. The main difficulty when using accelerometers data is to accurately determine the exact time points of foot landing and take-off, needed to compute the contact time. Several criteria have been proposed in the literature (see e.g. [16]), which are mainly empirical and based on extensive testing on a large number of athletes. Typically, the contact time is estimated from the vertical acceleration signal only, as in Fig. 4 (see [17]), or by computing the acceleration magnitude vector and empirically setting up an acceleration values threshold to identify the time interval of the foot ground contact (see e.g. [18]). The same accelerometer data can be used to compute the flight time, the stride frequency, and the stride length, if the space covered is known.

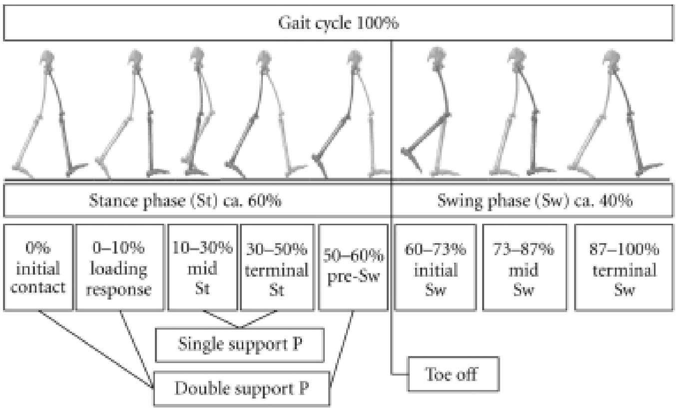

Fig. 3. A typical gait cycle.

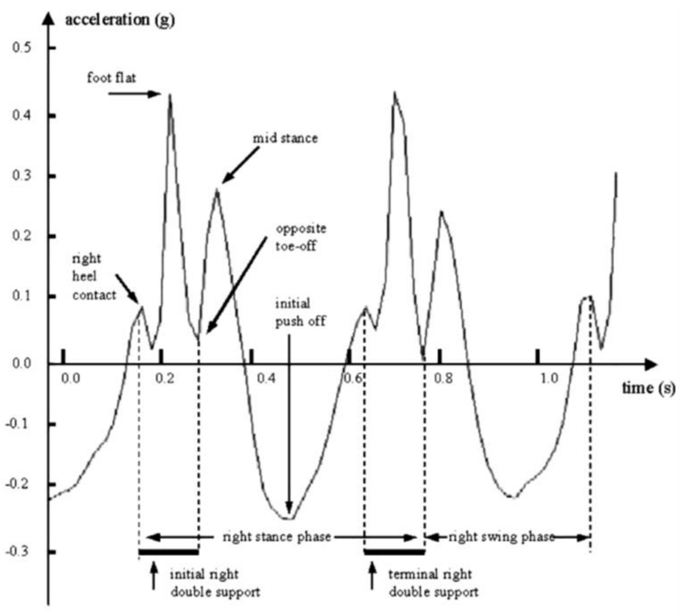

Fig. 4. A typical unbiased vertical acceleration profile for contact time estimation [17].

Remark 1: Note that all the gait cycle parameters may be different for different sport players and/or environmental conditions, and different reference values have to be considered when a walking rather than a running performance is investigated.

IV. Gait Measurements

Adopting a single-subject design procedure, a SensorTile board is placed on a runner's right ankle to obtain the accelerations along the three orthogonal leg axes: vertical, longitudinal and transverse (see Fig. 5). In order to reduce the relative movement between the device and the ankle, a neoprene rubber sheet is applied under the board. Even though the main content of human activity occurs below 20Hz, all the signals are acquired at a sampling frequency of 1 kHz , with a 12-bit resolution and a ±16g full scale range, which are typical choices for identification purposes on running experimental trials (see also [11]).

The accelerometer-derived data are preprocessed on a PC using a 5th order Butterworth filter (100 Hz cut-off frequency), in order to reduce the signal noise produced by the device vibrations due to an imperfect body fixing.

A. *Features Extraction and Activity Recognition*

In this section, some characteristic features are extracted from *running and walking* experimental tests in order to derive synthetic activity indicators. The signals shown in Fig. 6 are related to three orthogonal (one vertical and two horizontal) filtered ankle accelerations. It is clear the contribution of the gravity acceleration (vertical acceleration) and the standing, the running, and the walking phases are visibly distinguishable.

Say a_z the segment of the vertical acceleration signal related to a walking or a running phase, and N the number of samples in each walking/running instance, the mean value can be computed as:

$$\mu(a_z) = \frac{1}{N}\sum_{i=1}^{N} a_z(i) \,, \tag{1}$$

while the root mean square value as:

$$RMS(a_z) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |a_z(i)|^2} \,. \tag{2}$$

The separation between the two phases can be performed through a threshold on the mean (and/or the root mean square) values, which can be set from the evaluation of the parameter (1) (and/or (2)).

Fig. 5. A SensorTile mounted on the right ankle of an athlete's foot. Positive directions of the accelerometer local axes are indicated.

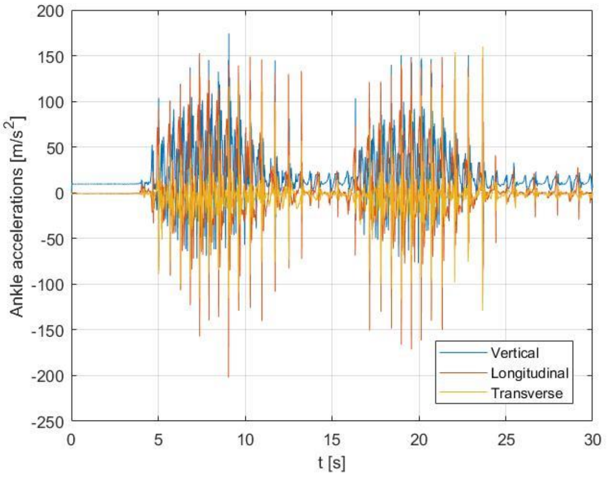

Fig. 6. Ankle accelerations experimental results during a running and walking test.

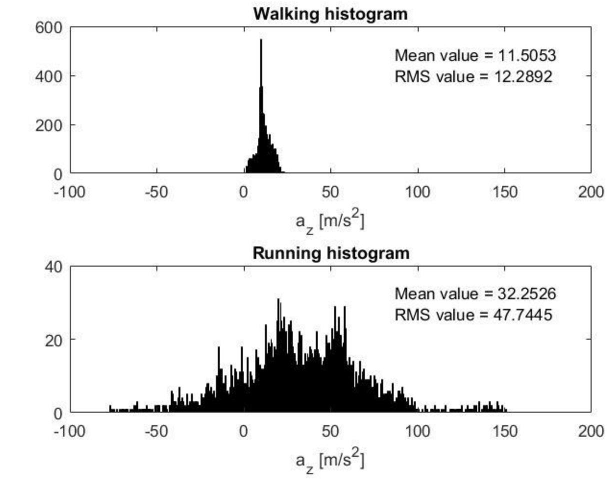

Fig. 7. Occurrence histograms for the walking and running instances.

The occurrence histograms for the vertical acceleration during the walking and the running phases are reported in Fig. 7. It is possible to discriminate the two activities by evaluating the corresponding mean values and/or root mean square values.

The initial standing phase (see Fig. 6) needs to be discriminated through a different statistical parameter, since the mean (root mean square) values are now close (see Fig. 8). The standard deviation is a more suitable feature in this case, and it is computed as:

$$\sigma(a_z) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|a_z(i) - \mu|^2}. \qquad (3)$$

Indeed, for the standing phase a standard deviation of 0.057 is obtained, compared to a 5.08 value for the walking phase. The discrimination between the two situations can be performed by setting a threshold on the standard deviation parameter (3).

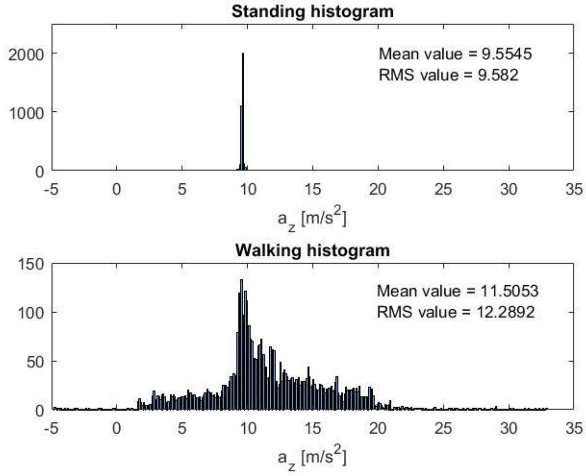

Fig. 8. Occurrence histograms for the standing and walking phases.

Remark 2: To detect very similar situations, such as walking upstairs or downstairs, the considered statistical parameters can be not adequate and a more sophisticated analysis can be needed, e.g. a better insight can be obtained by evaluating the power spectral density of the accelerometers signals. However, these issue is beyond this paper scopes.

Remark 3: Instead of using a (constant) threshold based classification criterion, which suffers from the variability of the data, the computed statistical features can be used to train an artificial neural network (ANN) in order to perform an automatic activity recognition (AAR). To this end, a recorded accelerations data set is used in [19], which is made available in [20] for research purposes. Starting from the experimental data, the Matlab™ environment is employed to design an ANN as first step before transferring the AAR system to the MCU (see also [21]).

B. Gait Parameters

Once the activity of the athletes has been recognized by using one of the synthetic statistical parameters described above (or an ANN has been trained in order to discriminate among some possible activities), the acquired acceleration data can be segmented into instances, each one related to a particular classified activity. The main gait parameters, associated to the detected activity, can now be determined from the accelerations frame data and numerical procedures can be designed for their computation.

There are several methods available in the literature concerning the gait parameters determination based on accelerometric data. In [22] four different criteria are compared for the stride time calculation starting from leg accelerations measurements. All the considered approaches are aimed to identify the impact times by a time domain analysis and provide very similar results. Remarkably, one of the proposed methods is particularly suitable for real time implementation, but requires a low pass filtering of the acquired signals with a custom designed cut-off frequency.

A first indication about the stride frequency can be alternatively derived by examining the magnitude Fourier spectrum of one of the acquired accelerations frame. In Fig. 9 the magnitude Fourier spectrum of the longitudinal acceleration related to a walking frame is reported. A first significant component at about 0.77Hz is present, which indicates a stride period estimation of about 1.30s. Analogously, in Fig. 10 the magnitude Fourier spectrum of the longitudinal acceleration related to a running frame is reported. A first significant component at about 1.75 Hz is present, which indicates a stride period estimation of about 0.57s. To improve the parameter estimation, high-pass and low-pass filters can be adjusted so as to limit the frequency range of the sensors to the range of interest only, aiming at reducing the contribution from high (vibrations) and low (gravitational field where not needed) frequency noise.

The determination of the ground contact time requires a more complex and in-depth analysis. Obviously, both the swing and the stance phase can be assessed once the time instants of the foot landing (heel or forefront strike) and take-off (toe-off) events have been recognized.

When the foot impacts the ground, with either a heel strike (walking) or a forefoot strike (running), an abrupt change in velocity occurs, i.e. a prominent peak in the accelerations arises (see e.g. [22],[23]). In [23], the foot landing event is identified by the maximum peak of the acceleration resultant vector modulus, while the toe-off time instant is found by locating, after each ground impact, the instant where the longitudinal and transverse accelerations simultaneously present a local maximum and minimum respectively (coherently with the axes orientation assumed in Fig. 5). However, such an approach gives an overestimation of the ground contact (see Fig.2 in [23]).

By considering the gait mechanism in detail (see [7]), the foot landing and take-off events are also characterized by the triggering of damped oscillations of the leg muscle-skeleton system, whose starting point can be recognized by one of the ankle acceleration signals (the phenomenon is particularly evident in the foot landing case and during running).

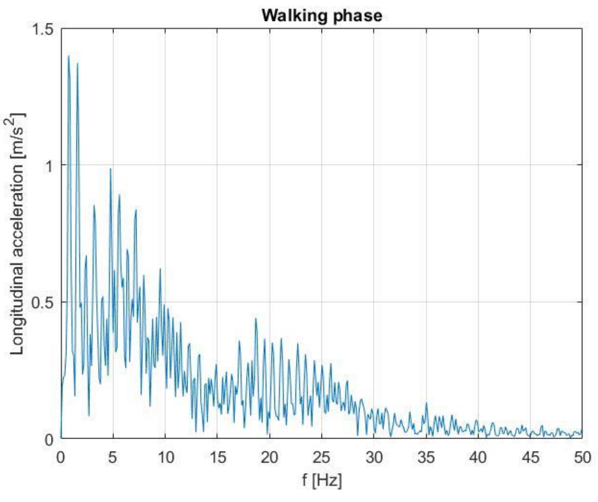

Fig. 9. Magnitude spectrum of the longitudinal acceleration of a walking instance.

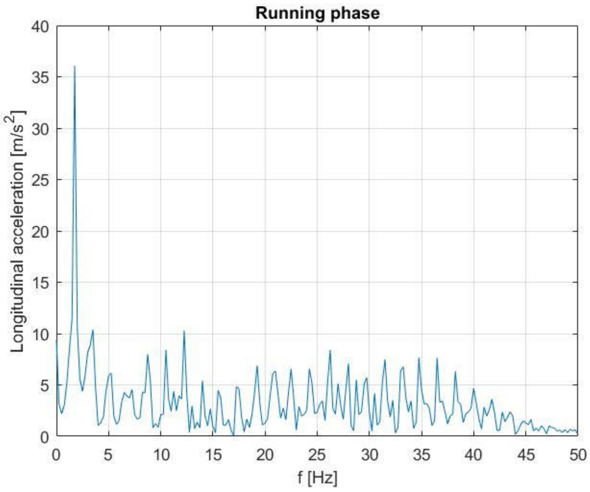

Fig. 10. Magnitude spectrum of the longitudinal acceleration of a running instance.

As a result, the foot landing event can be identified by the minimum peaks of the longitudinal acceleration only (or by the minimum/maximum peaks of the transverse/vertical accelerations). For the foot take-off, the toe-off event may be discriminated by the local minimum of the longitudinal acceleration (or by the local minimum/maximum of the transverse/vertical accelerations).

In Fig. 11 the assessment of the stance phase and of the swing phase durations is reported for the walking phase. The stance phase lasts about 0.72s, while the swing phase lasts about 0.57s. A stride period of about 1.29s is then calculated, which is in accordance with the stride period value previously estimated through the frequency domain analysis.

In Fig. 12 the assessment of the stance phase and of the swing phase durations is reported for the running phase. The stance phase lasts about 0.11s, while the swing phase lasts about 0.46s. A stride period of about 0.57s is then calculated, which in accordance with the stride frequency values previously estimated through the frequency domain analysis.

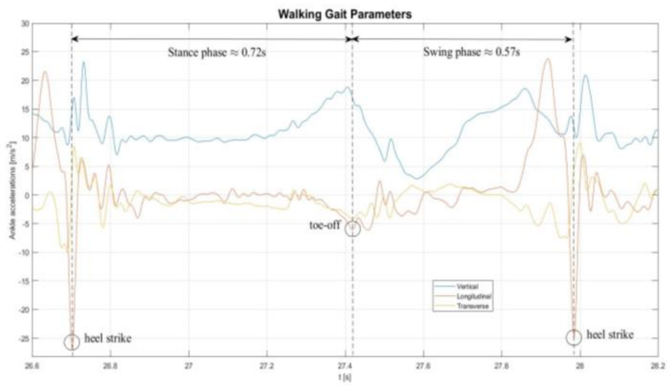

Fig. 11. Walking gait parameters estimation from the accelerometers data.

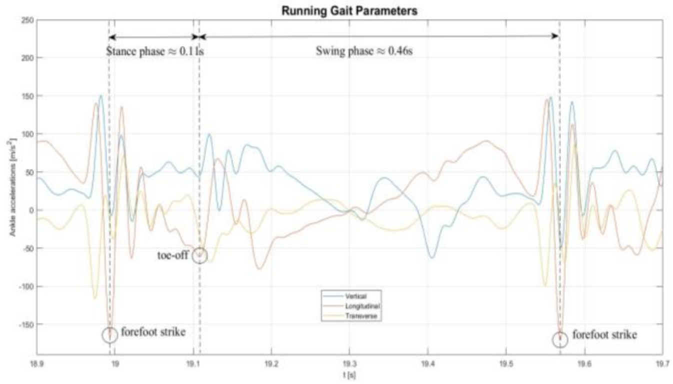

Fig. 12. Running gait parameters estimation from the accelerometers data.

V. Conclusions

In this paper, the potential of a wearable device for the monitoring and the performance analysis of running athletes has been examined. Tri-axial accelerometers (MEMS) have been adopted to generate the data to elaborate for assessing the main gait parameters during walking or running road-tests. The analysis of the experimental results related to a series of walking and running trials has led to the definition of some synthetic (statistical) parameters which have been used to discriminate among the standing, walking and running activities of the athletes.

Moreover, the study of the gait mechanism has allowed defining a procedure to detect the ground contact time parameter, by identifying the time points of the foot landing (heel or forefoot strike) and take-off (toe-off). Both a frequency domain and a time domain approach have been implemented for the computation of the stride frequency during the walking and the running phase, providing comparable results. The computation of the ground contact time has been performed by using a simple elaboration of the longitudinal acceleration only, that can be implement in the MCU of the considered device without effort.

In our future developments, an experimental campaign involving athletes of different sex, age, training and health conditions will be carried out in order to derive possible (statistical) relationships with the computed gait parameters.

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