Wearable Biometric Performance Measurement System for Combat Sports

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Abstract:
This paper presents the design of a wearable system for measurements of athlete's performance in combat sports. The system provides objective measurements of athletes' shots, posture, and movements, and of the effectiveness of their training. The proposed instrumentation is useful to overcome the limits of traditional training methods, which are characterized by a subjective evaluation of the training effectiveness by a coach. The measuring system consists of a distributed network of three battery-powered wireless-sensing node types, worn by the athletes, and one master node, which is in charge of signal acquisition and processing tasks. The master node elaborates training statistics and visualizes them, either in real time during a combat session, or off-line for posttraining analysis. The wearable measuring system has been tested through real combat training sessions of athletes with different weights, ages, and experiences, both male and female. Different from the state-of-art athletes' biometric measurement machines, which are cumbersome and expensive, the proposed system is designed to ensure a low-cost and wearable implementation and to give easy-to-understand feedbacks during training, particularly to nonprofessional athletes.

SECTION I.

Introduction

The training of athletes in combat sports aims at improving the effectiveness of their shots and movements. Traditional training methods foresee a subjective evaluation of the effectiveness of the training by a coach. At the state of art, some measuring machine exists to provide an objective measure of athletes' performance. However, the cost of these machines is too high for nonprofessional athletes.

On the other hand, wearable and low-cost measuring devices, developed in the last years for health and wellness applications, do not fit the requirements of combat sports. They give feedbacks about heart and breathe rate, running speed and distance, number of steps, and estimation of burned calories. Instead, combat sports require the development of devices able to provide an objective measurement of the effectiveness of punches and/or kicks, which entail high acceleration levels.

The energetic analysis and the momentum are the simplest ways to study one hit, but they are hard to correlate with an anatomical damage of a hypothetical human body. Therefore, these methods can give a false evaluation of the hit effectiveness. According to Fig. 1, a performance measurement system for sport training has the following targets: 1) giving an automatic feedback during training to understand which corrections should be made to optimize the athletes' movements and 2) defining the training program of each athlete.

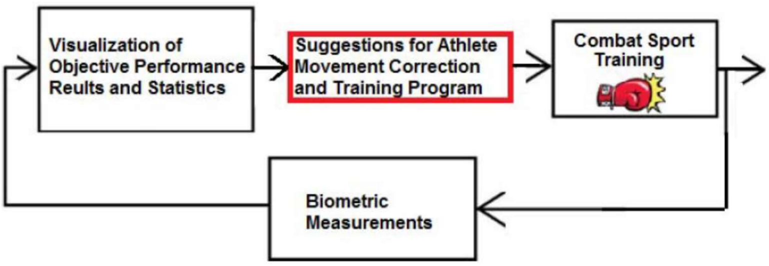

Fig. 1.

Performance measurement system for sport training.

With respect to this long-term result, the focus on short-term research is to provide a cost-effective measurement of athletes' biometric performance, and to elaborate and visualize, in real time, their statistics (black boxes in Fig. 1). To address these issues, this paper presents a wearable measuring system, which aims at correlating the strength of the hit, with the effectiveness of the leg/arm movement and the damage caused to the sparring partner. To address also the market of nonprofessional athletes, the proposed system is cheap, based on Components Off The Shelf (COTS) sensors and signal-processing devices, and operates in real time.

Hereafter, Section II reviews existing measuring devices for sport performance measurements, proposed by academia and/or industry, and analyzes their limits. Section III discusses the physical quantities to be analyzed for an objective measurement, in real time and with limited cost, of the combat training effectiveness. Sections IV and V present the architecture definition and the design of the wearable sensing and measurement system. Section VI shows and discusses experimental tests carried out during real combat training sessions. Conclusions are drawn in Section VII.

SECTION II.

State-of-Art Review for Combat Sports Biometric Measurements

At the state of the art, several works provide instrumentations for biometric performance measurements of athletes. However, most of them [1]–[2][3][4][5][6][7][8][9][10][11][12] are not suited for combat sports that are characterized by high acceleration levels and by fast movements of upper and lower limbs. Moreover, combat sports require the measurement of the strength of each hit (punch and kick). Specific devices for performance measurements of athletes in combat sports have been proposed [13]–[14][15][16][17][18][19][20][21][22][23][24][25][26][27], but they are characterized by several limits, listed hereafter.

1. Most of commercially available measurement systems have a price of 2000 USD or higher [22]. This price limits their usability to professional athletes with sponsors, or athletes hired from the armed forces. The target price for nonprofessional athletes should be below 1000 USD.

2. Many available devices for athletes' performance measurements exploit only biometric parameters such as force, without any measure of the acceleration profile in three dimensions of the upper or lower limbs. For example, to monitor the frequency and magnitude of punches or kicks thrown by a single athlete, a load cell

can be sandwiched between two aluminum plates, embedded in a training bag [18], [21], and attached to a stand or installed onto a rigid wall. When the athlete throws the punches or kicks, the impact force is applied onto the force sensor. The output of the sensor is digitized, and then is transferred to a host PC. A software, running on the PC, counts the number and amount of the perturbation from zero, and displays this information to the athlete/coach on a monitor.

3. Most of available instruments [18], [21], [24] are not wearable, and cannot be used to measure in real time the biometric performance of the two athletes involved in a combat training session or in a combat match.

4. Some of the sport measuring devices proposed in the literature adopt a complex array of video cameras [10]–[11][12][13][14][15], [24]–[25][26]. The idea is to acquire and process video streams to detect athletes' movements for automatic scoring in professional matches of specific sports, such as boxing. However, video-based signal processing requires power hungry platforms if realized with software programmable hardware. On the other hand, the development of dedicated integrated circuits is not feasible in a niche market such as that of sport measurements. The use of video cameras for accurate biometric and motion analysis requires good illumination conditions, which are difficult to guarantee for outdoor training sessions.

5. Low-cost (hundreds of USD) and wearable sensors for combat sport measurements have been announced for 2017 in [20], but in this case, the analysis is limited to the acceleration of the upper limbs through sensorized armlets. The system in [20] does not take into account the deformation caused on the target, and which part of the body of the sparring partner has been hit. Moreover, movements of the lower limbs and posture of the athletes are not analyzed in [20].

Wearable devices to measure biometric parameters have been proposed in the literature for health applications [28]–[29][30][31][32][33][34][35][36][37][38][39][40][41][42][43][44][45]. However, they are suited mainly for remote monitoring of vital signs at home or for health/wellness when running: they provide functions, such as the measurement of heart-rate and breath-rate, burned calories, running speed and distance, number of traveled steps. Some of them include also altimeter and terrain slope estimation. Wearable devices for health measurements can provide also functions, such as fall detection (for elderly people), electrocardiography measurements, body temperature, levels of oxygen (SpO2), and glucose (glycemia) in blood. However, these systems are not suitable for combat sports. Indeed, as discussed in Section III, the objective measurement of a hit requires the measurement of high acceleration levels and of the deformation caused on the target. All of the above-mentioned devices lack the possibility to give the fighter, at low cost, a feedback to adjust his combat technique or his way of moving.

This paper extends the IEEE MEMEA2016 conference contribution [23] in terms of detailed review of the state-of-art, inclusion of the evaluation of the posture of the athlete and its motion activity (missing in [23]), and the analysis of strength and dynamic for kicks and punches (only punches in [23]). In this paper, a larger set of experiments during real athletes' training is used to test and characterize the system. Moreover, [23] uses custom subgigahertz links to connect the sensing nodes with the gateway node, whereas in this paper, bluetooth low energy (BLE) wireless technology is used. Operating at 2.4

GHz, with 1-MHz/channel bandwidth, a BLE link allows a data rate of 1 Mb/s, one order of magnitude higher than in [23]. The increased bandwidth is useful to transmit data from multiple sensors, placed in different parts of the body (e.g., at wrist, ankle, hip, elbow, and knee), and not only at wrist as in [20] and [23].

SECTION III.

Measuring Quantities for Combat Sports

Which physical quantities play a role to evaluate the effectiveness of a hit, and how measuring them at low cost and in real time are still open issues in the literature. The pressure exerted by the hit on the target's body is one of the most suited candidates. By measuring and processing it in real time, and by using models derived from traumatological studies, the extent of damage from the anatomical point of view can be estimated. As a consequence, the effectiveness of the athletes' movements and training can be evaluated.

Beside the measurement of the pressure on the target's body, the proposed system aims also at measuring the acceleration profiles of the athletes. This quantity is important to analyze wrong trajectories (i.e., deviations from the ideal path depending on the strike) and any increase in the stiffness of the hitter's arm (or leg), which prepares himself to the impact but reduces the speed. Indeed, many inexperienced fighters have a better feeling of power when delivering strikes with twitched muscles during the whole action. Often, it is difficult for coaches to persuade them that they need to keep the body as relaxed as they can to reach higher speed and higher power levels. Measuring the acceleration profile of the arm/leg is a faster and easier way of teaching nonprofessional athletes, instead of traditional methods based on subjective analysis and fighting experience.

The proposed instrumentation allows the measurement of time and force of the strike and acceleration profile of the arm or leg. The time taken to give a punch, or a kick, depends on the type of combat sport, on the adopted technique, on the specific athlete. Anyway, its order of magnitude amounts to tenths of seconds. The acceleration of the hit is in the order of the dozen times the gravity acceleration g . As far as the exchanged force is concerned, studies in the literature on boxers estimate the limit of compressional force delivered by a boxer around 5000 or 6000 N on a ten squared centimeters area. Due to these values, a realistic upper limit for the force of a kick is 12 000 N, which is twice that of a punch. The use of acceleration measurements has been proposed in [11] and [20], but in [11], it is limited to a single axis. Instead, as discussed in this paper, the measurement of all three axis is important. Moreover, in [11] and [20], the deformation caused by the punch or kick is not taken into account. Another parameter to measure, and to correlate to the other acquired data, is the posture of the athlete that delivers the shot and that of the athlete that receives the hit.

SECTION IV.

Measurement System Architecture

A. General Architecture

The market of performance measurement systems for combat sports is a niche market. Since it is not affordable, the high development time and cost of application-specific integrated circuits, an approach based on COTS devices, are used to reach the desired tradeoff between performance and costs. The proposed measurement system consists of a distributed network of four types of nodes: three sensing nodes to be worn by the athletes during training, and one sensor acting as a gateway. The latter is in charge of tasks, such as data acquisition, local signal processing, and transmission toward visualization devices, e.g., an LCD display, or toward remote hosts. Considering a ring of size L×L (with L from minimum 6 m to maximum 8 m), the gateway node is at the ring border, connected via a wireless link with the sensing nodes, which are worn by the athletes. The distance between athletes and the gateway node is some meters. At the ring border, there are also the LCD display for visual feedbacks and the Flash memory, storing all data for off-line future analysis. All acquired data and processed statistics, via wireless or wired links (Wi-Fi or Ethernet), can also be transmitted to a host PC and to other video terminals, which can be placed where desired, near the ring or in a remote position.

B. Sensing Node Types

The first node type (type A) measures the accelerations of upper or lower limbs (or both, depending on the combat sport) of the athlete under training. The aim is tracking the movements of the kick or punch. Each of this node is a battery-powered wireless sensor, worn as a wristwatch, armlet and/or anklet, measuring three-axial accelerations. The transmission toward the gateway node (at the ring border, at a distance of few meters) is wireless, via a BLE connection, using a 2.4-GHz antenna directly printed on the PCB. With respect to the subgigahertz connection adopted in [23], the BLE link allows higher compatibility with other systems. The main features of BLE are the following: 1) the data rate can be up to 1 Mbps; 2) the connection distance is up to 100 m in outdoor line-of-sight conditions and is several meters in indoor conditions; 3) the communication latency is low, only few milliseconds; 4) the power consumption is limited to few tens of milliwatts. The worst case for power consumption is when transmitting: a current well below 15 mA is drained from a power supply of few volts. By implementing power cyclic techniques (the transceiver is ON only when transmitting data), the energy cost is minimized. The BLE natively supports security technologies, such as 128-b advanced encryption standard, and robustness techniques, such as adaptive frequency hopping, lazy acknowledgment, 24-bcyclic redundant code, and 32-b message integrity check. The number of sensors of the type A, worn by each athlete, depend on the specific sport. For example, two nodes are required in the case of boxing, for kick-boxing at least four nodes are needed.

The second type of measurement node (type B) consists in an array of strain gauge sensors used to sense the deformation under the kick or punch of a thin aluminum plate. The plate should be worn by the sparring partner during training or by each of the two athletes during a combat match. This node is battery powered and has a BLE wireless transmission capability toward the gateway node. Depending on the combat sport type, just a thin plate should be worn to cover the chest, or multiple smaller thin plates should be worn to cover the parts that in the specific sport can be hit. For example, in the case of kick-boxing, about ten sensing aluminum plates have to be worn for chest, shoulders, legs, and arms. We consider that for training combat sports, the head should not be hit, and hence the head is protected through a nonsensorized helmet.

The third sensing node type (type C) embeds both the functionalities of a motion sensor and of an electrogoniometer, thus detecting the motion activity and the joint angle (of knee, elbow, and so on). This node type, completely missing in [23], is detailed in Section V.C and is equipped with posture estimation algorithms. This sensing node can be worn through a belt near the hip, or through a knee-pad to measure the knee-angle or similarly the elbow-angle. Nodes of types A–C mainly require sensing and wireless communication capabilities at low size and low power consumption. For the sensing nodes, the requirements in terms of computational power and memory size are limited. When developing the above-mentioned nodes, to save memory space on the embedded platform, an operating system has not been used. Instead, a library of basic software functions has been designed for sensor signal acquisition and for calibration. The software also includes communication functions to drive the BLE transceivers. For these low-level implementing software tasks, there is mainly a technical effort, while the innovation of this paper is related to the measuring system architecture, the sensor signal processing algorithms, and the results of the experimental test campaign.

C. Gateway Node

The last node type (type D) is a gateway [see Fig. 2]. It is not a wearable node, but it is placed at a distance of few meters from the athletes, e.g., at the ring border. It collects the data coming from the wireless sensors of the first three types and implements local signal processing to calculate athlete performance statistics. Tens of signals are acquired. For example, for each athlete during a combat training of kick-boxing, four sensors of type A, eight sensors of type B, and up to six sensors of type C can be used. The cost of each node for a series production, using the components detailed in Section V, is estimated in few tens of USD. Therefore, even in the case of a rich configuration, the cost of the whole system can be kept around one hundred of USD. Obviously, the price of some thousands of USD of commercial products [22], which includes not only the device and material cost but also other costs (labor, marketing, and so on), cannot be directly compared with the cost of a laboratory prototype. However, avoiding the use of array of video cameras, and of expensive custom sensors, the proposed measuring system, if commercialized, can be sold in the market at a price well below the target 1000 USD. The number of sensors of types A and C can be halved if only the preferred part (left or right) used by the athlete to provide a shot is monitored. The number of sensors of types A and C can be further reduced if only upper or lower limbs are monitored.

The gateway node (type D) saves the acquired data in a Flash memory so that the training data can be analyzed off-line when the match is closed. The gateway node also analyzes in real-time hit statistics during the match to properly assign points to the athletes and drives a proper graphical user interface for a visual feedback of hits, their force, and their acceleration. Moreover, the processed data can be transmitted to a remote unit through the Internet. Different from [23], in this paper, the gateway node also elaborates and visualizes data related to the posture of the athlete and to the joint angles and accelerations of hip, knee, and elbow. Such information, combined with data on acceleration and on strength of punches and kicks, allows an exhaustive analysis of the athlete movements. Moreover, the gateway node can store in lookup tables (LUTs) precalculated traumatological maps of the body with different scores. When the information about the strength and acceleration of the shots, and of the part that has been hit (generated by sensors of types A and B), is acquired by the gateway, the score of the combat training or match can be calculated by applying a weight depending on the LUT. This way, the real effectiveness of the shot during a match or training is evaluated. The LUT can be modified by an expert (coach, judge, and athlete), according to the different rules of the combat sports, or according to the different training programs.

The gateway node has reduced constraints in terms of power consumption with respect to the sensing nodes, but it has an increased cost in terms of computational power and memory requirements. The gateway node can be in its turn connected through a local USB port or through Internet (cabled LAN or wireless Wi-Fi) to a remote PC acting as a server. The gateway node has been implemented as a custom printed circuit board equipped with 32-b ARM Cortex processor, 1-GB RAM memory, 4-GB Flash nonvolatile storage, BLE chipset, network connectivity (e.g., Wi-Fi, Ethernet, and USB), and Android OS.

SECTION V.

Sensing Acquisition and Processing System

A. Acceleration Measurement

To sense the three-axial acceleration profile of the leg or arm, the accelerometers (type A nodes) should have these features:

1. bandwidth in the order of hundreds of hertzes;

2. sensing range in the order of a hundreds of g (1 g = 9.81 m/^{2}).

The Sparkfun ADXL377 accelerometer has been selected to fulfill the above-mentioned requirements. It is capable of a detection range of ±200 g and has a user-configurable bandwidth, from dc to 500 Hz in our implementation. This sensor is a polysilicon surface-micromachined structure built on top of a silicon wafer. Polysilicon springs suspend the structure over the surface of the wafer and provide resistance against acceleration forces. Deflection of the structure is measured using a differential capacitor that consists of independent fixed plates and plates attached to the moving mass. The ADXL377 uses a single structure for sensing the acceleration in the x -axis, they -axis, and thez -axis. As a result, the three sensor directions are highly orthogonal with little cross-axis sensitivity. The ADXL377 has a 320-kΩ resistance on each amplified output. The bandwidth of the device can be set by simply adding a single capacitor on each of the three outputs. By using three 10-nF capacitors, a low-pass filtering effect is obtained with a cutoff frequency of 500 Hz. This value has been determined considering that the typical time constants characterizing athletes' movements are higher than 2 ms when boxing or kicking. Hence, the frequency of interest for the biometric measurement system is within the spectrum range from dc to 500 Hz.
The accelerometer signals are acquired through the 12-bit SAR ADC integrated in an embedded controller which is based on a 8-b ATmega328P microcontroller, including also 1 Kb of EEPROM, 2 Kb of SRAM, and 32 Kb of Flash memory. It has 14 digital input/output pins (of which six can be used as PWM outputs), six analog inputs, a 16-MHz quartz crystal, a USB connection, a power jack, and a reset button. The embedded system is powered at 3.3 V through a lithium battery. The accelerometers have to be worn as armlet or anklet or wristwatch. They are battery powered; a BLE wireless chipset is used to exchange data with the gateway node in Fig. 2.

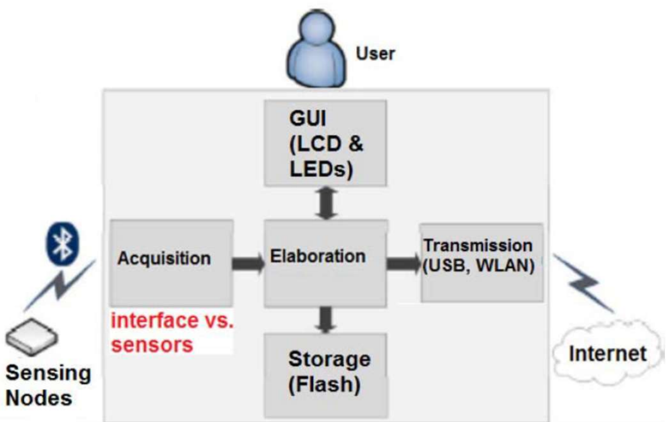

Fig. 2. Main building blocks of the gateway.

B. Compressional Force Measurement

To measure the compressional force per area of the kick or punch on the target (type B nodes), the deformations of a known surface, worn by the athletes, has to be measured. To this aim, a matrix of strain gauges can be used to get the applied forces' distribution. The area of application can be evaluated through a regression algorithm. The surface on which the punch or kick is applied needs to stay in his elastic deformation range to perform multiple reading. At this point, we can rewrite the problem as the choice of a specific material for building a plate of adequate thickness. Then the following steps are followed: i) characterize the deformation of the wearable plate with known forces and application's area; ii) use simulations and a mechanical compression test to formulate the regression algorithm. To perform this choice ANSYS, an FEM (Finite Elements Modeling) software, has been used to build the simulation of a pressure on plates of various materials using the approximation of half-spherical, and normal to the surface, pressure distribution. Fig. 3 shows for example the ANSYS simulation for the pressure detected, before [Fig. 3(a)] and after [Fig. 3(b)] a kick-shot, on an aluminum plate of size 200 mm ×100 mm, with a mesh of 512 elements, each of 40 mm^2. In Fig. 3(a) the magnitude color levels correspond to a shot strength from 0 N (blue region) to 12 000 N (red region). In Fig. 3(a) (at rest) to show lower values, the magnitude color levels correspond to a shot strength from 0 N (blue region) to 2000 N (red region).

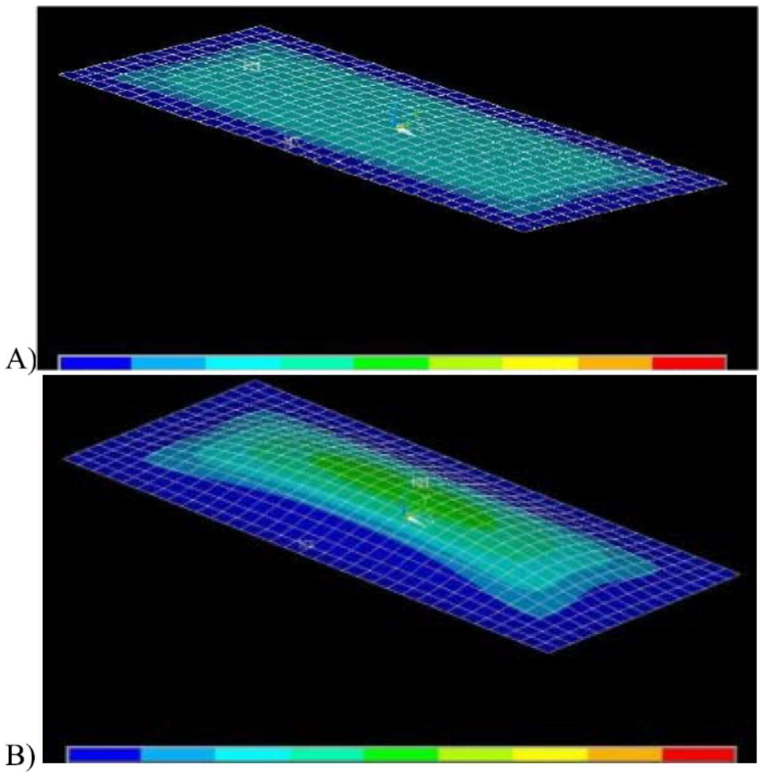

Fig. 3. Pressure levels of a thin aluminum plate. (a) Before a shot (color scale from 0 N (blue region) to 2000 N (red region)]. (b) After a shot [color scale from 0 N (blue region) to 12000 N (red region)].

Another idea is the use of wearable shirt made in e-textile to sense the pressure of the hit. This design suffers the hard problem of regressing from the deformation to the applied force per area measurement, but it will add the possibility of building a full wearable device and then discriminate if a hit would be effective or not during a competition. This could substitute the actual scoring system based on the contact's kind with a more appropriate system based on the effectiveness of the hits. An alternative to the use of distributed strain gauges on the plate to be worn by the athlete can be adopting a load cell, such as the CZL204 button load cell, facing up to 1000 kg.

In the rest of this paper, the experimental activities have been carried out using the wearable aluminum plate as compressional force measurement device. To acquire the strain gauge sensors' signals a 24-bit sigma-delta ADC, the HX711 from Sparkfun, has been used. The ADC is controlled via I2C by an embedded microcontroller, the same already used and described in Section V-A for acceleration measurement.

C. Custom Mobility Sensor

A third sensing node (type C), a custom mobility sensor to study the movement of body and detect if the posture during training is correct or not has been developed. It is a new developed sensor able to extract several parameters: fall detection, static detection (no movement is detected), step detection and stride estimation, and joint angles of hip, elbow, and knee. Thanks to these data, the correctness of the posture of the athlete during training can be also evaluated.

The custom mobility sensor is light and small enough so that it can be worn, typically at the hip through a belt, and at the knee and elbow through knee/elbow-pads, without any impairment of the training sport activities. Its size (see Fig. 4) is comparable to a coin of cents of Euro. The sensor is equipped with a System in Package (SiP) device containing a nine-axis MEMS inertial measurement units (IMUs). It contains a three-axial gyroscope, a three-axial accelerometer, and a three -axial digital compass. Following the approach in [46] and [47], by properly processing information from the accelerometers, an electrogoniometer function is achieved (measurements of joint angles). This way the complexity of the measuring system is reduced versus the state-of-art approaches using additional sensors, such as potentiometers, strain gauges, or optical devices to measure the joint angles [48]. Communication with the gateway is based on a BLE chipset, integrated into the device, like the other sensors. A 32-b ARM Cortex-M processor is used to fuse in the digital domain the information coming from the three sensors (gyroscope, accelerometer, and digital compass). The power consumption is about 10 mW for the processing core and less than 300 mW for the whole smart sensor (9-D sensor plus processing and communication chipsets) in typical conditions. The sensor can be supplied at 3.3 V draining a current less than 90 mA in worst case. Therefore, a typical Li-polymer battery pack of a smart phone (e.g., the ASUS 11.5-Wh C11P1501 battery) can supply the device for about 40 h, i.e., about two months without needing recharge for a nonprofessional athlete with a training program of 5 or 6 h per week.

Fig. 4.

Motion sensor.

Two built-in algorithms run on the device: the first, computing the step detection and the estimation of the stride length (SL); the second, determining the fall detection or no movement revelations. Instead, a posture estimation algorithm runs on the gateway node. The two adopted algorithms, running in the custom mobility sensor, are briefly described hereafter.

The first algorithm, implemented for step detection, consists of four main stages. In the first stage, the magnitude of the acceleration a_i for each sample i, captured by the accelerometer, is computed. In the second stage, the local acceleration variance is computed to remove gravity. The third stage uses two thresholds: the first (T_1) is applied to detect the swing phase, whereas the second (T_2) is applied to detect the stance phase (B_{2i}) in a single step while walking. The fourth stage detects when a swing phase ends and a stance phase starts.

Estimating the SL for each detected step can be useful during sport training for the following:

1. the extraction of the speed information by multiplying the SL data with the frequency of steps;

2. the evaluation of the total movement of an athlete during the training phase;

3. providing a feedback of the movements of the two athletes during the combat training.

Generally, the SL depends on the person, its leg length, and the nature of the movements during walking. Hence, its estimation can be complex and costly to achieve in real time. Aiming at a real-time and low-cost implementation of the system, in this paper, we adopt the hypothesis proposed by Weinberg [30], which assumes that the SL is proportional to the bounce, or vertical movement, of the human hip. This hip bounce is estimated from the largest acceleration differences at each step. The algorithm implemented for SL estimation consists of the following two steps. The first step computes the magnitude of accelerations a_i. The second step estimates the SL using the Weisberg expression in (1) [29], where the maximum and minimum operations are applied over the filtered accelerations in a window of size $2w+1$ around the sample $i(p)$ corresponding to the p stance detection. In (1) K is a constant that has to be selected experimentally or calibrated. If the length SL, estimated by the above-mentioned method, and the frequency of the *step* is known, it is possible to derive the velocity of each step as the product of the two parameters

$$SL = K \sqrt[4]{\max_{\tilde{a}_j,\, j=(i_p \pm w)} - \min_{\tilde{a}_j,\, j=(i_p \pm w)}} . \quad (1)$$

The second built-in algorithm, implemented to determine the fall detection, is based on the controls of some thresholds. Indeed, a fall-like event is defined as an acceleration peak of magnitude greater than 3 g followed by a period of 2.5 s without further peaks exceeding the threshold. The accelerometer-sampling rate has been set at 50 Hz, a tradeoff between resolution and power consumption. Threshold values around 3 g (ranging from 2.5 to 3.5 g), and of about 2 or 3 s, have been widely used in other fall detection systems [32]. The value 3 g is small enough to avoid false negatives, since real falls are likely to present an acceleration pattern containing a peak that exceeds such a value. The time interval of 2 or 3 s, without noticeable activity after an acceleration peak, to detect a fall is needed to distinguish it from a jump. In the case of jump, there are multiple high acceleration peaks within a window of 1 s [49].

Several sensor placements have been already tested, e.g., the waist, trunk, leg, hip, and foot. From our test, although data from all locations provided similar levels of accuracy, the hip was the best single location to record data for activity detection. It provides better accuracy than the other investigated placements [33]. This location also allows having a cleaner signal from the IMU. However, the exact position and orientation of the platform on the hip for fall detection are not important, because our algorithm only works with the magnitude of sensor readings. This facilitates the use of the system also in nonprofessional sport scenarios. The function for posture evaluation is running at the gateway-node side. It first acquires and visualizes several motion parameters for the motion sensors of type C (if the athlete is moving or is static, if a fall or a step is detected, the SL, the speed, and the angles of hip, knee and elbow) and of types A (accelerations at wrist and ankle). Then, by comparing these parameters with proper programmable thresholds, configurable by the coach through the GUI, an automatic evaluation of the posture as "good," "wrong," and "improvable" is implemented. This analysis refers to the state-of-art works, where posture is evaluated representing the athlete as a multisegment object (with five joints in our case, since we are interested in the effectiveness of punches or kicks: anklet, knee, hip, elbow, and wrist). The proposed system allows for posture analysis, but the threshold values have to be configured by the user (e.g., athlete, or better the coach or a sport scientist), and often are derived heuristically. Defining a biomechanical model for an automatic definition of these thresholds is out of the scope of this paper. In the proposed combat sport measuring instrument, the calibration can be done at component and system levels. At component level, since the instrument relies on COTS devices, the manufacturer's recommended "step" calibration procedure has to be followed. At system level, by modifying through the GUI, the above-cited thresholds, and the LUTs in Section IV-C, the instrument supervisor (e.g., the coach) can calibrate the system response, e.g., the summary indexes in Table II(a) and (b).

SECTION VI.

Experimental Measurements

A. Measuring Scenario

To test the proposed measuring system in a real scenario, several experimental trails have been done. Particularly, the training of nonprofessional athletes performing martial arts such as Karate has been selected as measuring scenario. The acquired data have been compared with subjective evaluation of the hits and movements by a coach and with the years of expertise and belt color of the athletes. Hence, it is possible to assess the correlation between the measurements of the proposed system and the real skill level of an athlete. Different Karate athletes, with different years of expertise and weight, have been considered. The current testing population amounts to about 70 people (64 athletes plus 6 coaches) of different weights, sexes, and colors of the belt, i.e., different levels of expertise. Several punch and kick tests have been performed, for each subject, with everyone's favorite arm or leg.

For the sake of space, this paper shows the results of seven subjects, representative of the testing population. Table I reports the identifications of the seven subjects, their characteristics in terms of age, weight, sex, color of the belt, and years of practice.

More in detail, Figs. 5–13 show the measured spatial displacement and speed, as a function of time, for five different movements, specific of the karate tradition: gyaku-tsuki, oi-tsuki, mae-geri, yoko-geri keage, and yoko-geri kekomi. Reported measurements refer to karate movements performed by the subject B25. For comparison, Fig. 7 shows the same gyaku-tsuki movement by the athlete Br6. Fig. 14 shows the considered coordinates for the experimental tests (in the case of a punch). Table II(a) and (b) and Figs. 15–19 show the hit strength and the acceleration measured when performing a front kick and a front punch (toward the chest of the sparring partner) by all the seven athletes in Table I.

TABLE I
CHARACTERISTICS OF THE ATHLETES UNDER TESTS

SubjectID	Y1	O2	O3	Br6	B23	B21	B25
Belt, color	Yellow	Orange	Orange	Brown	Black	Black	Black
Sex	Male	Male	Female	Female	Male	Male	Male
Age, yrs	18	35	22	21	31	30	42
Practice, yrs	1	2	3	6	23	21	25
Weight, kg	62	101	50	60	72	86	75

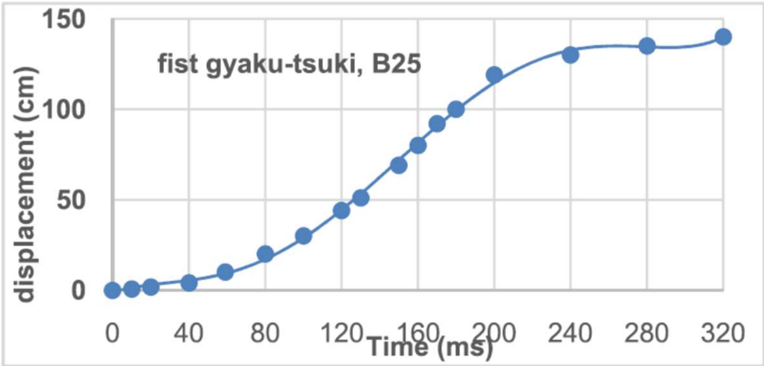

Fig. 5. Displacement of the fist projection, gyaku-tsuki, B25.

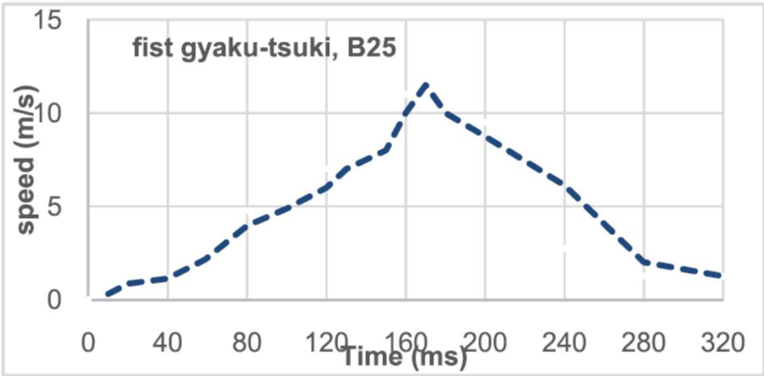

Fig. 6. Speed of the fist, gyaku-tsuki, B25.

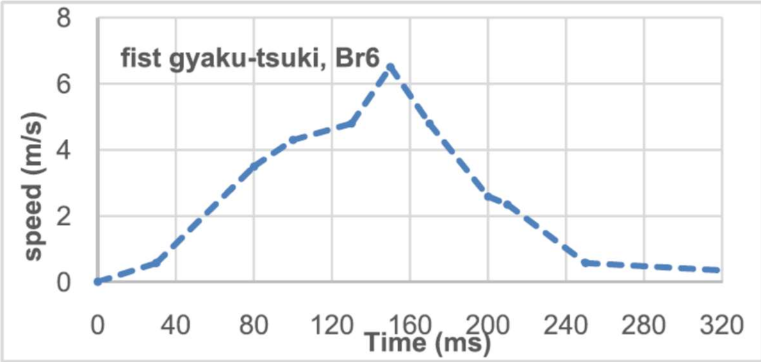

Fig. 7. Speed of the fist, gyaku-tsuki, Br6.

TABLE II

(a) MEASURED MAXIMUM STRENGTH FOR FRONT PUNCH. (b) MEASURED MAXIMUM STRENGTH FOR FRONT KICK

(a)

SubjectID	Y1	O2	O3	Br6	B23	B21	B25
Strength, kg	31	83	61	103	261	202	211
PSWR	0.5	0.82	1.22	1.72	3.63	2.35	2.81
Automatic feedback	Improvable		Good		Exc.	Good	

(b)

SubjectID	Y1	O2	O3	Br6	B23	B21	B25
Strength, kg	68	155	147	239	540	481	517
KSWR	1.1	1.53	2.94	3.98	7.5	5.59	6.89
Automatic feedback	Improvable		Good		Exc.	Good	

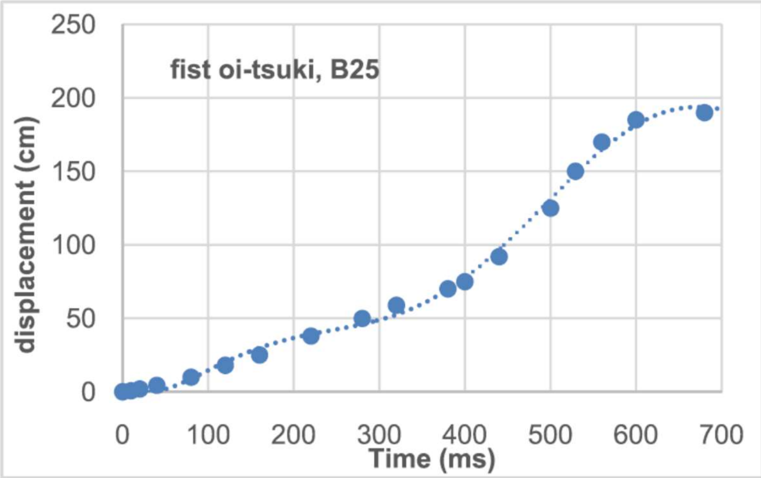

Fig. 8. Displacement of the fist projection, oi-tsuki, B25.

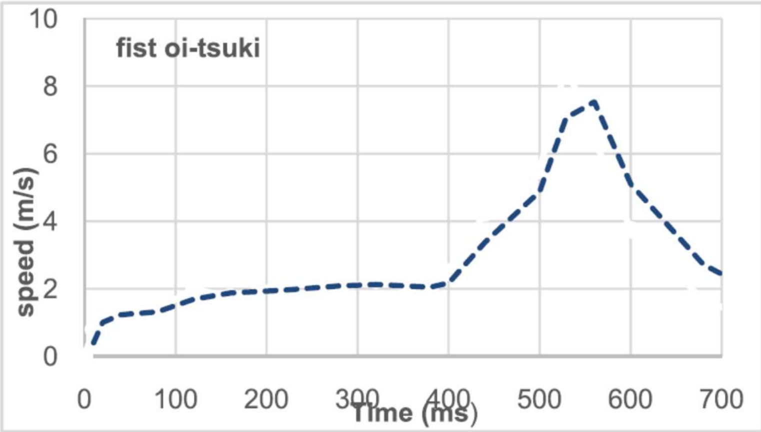

Fig. 9. Speed of the fist, oi-tsuki, B25.

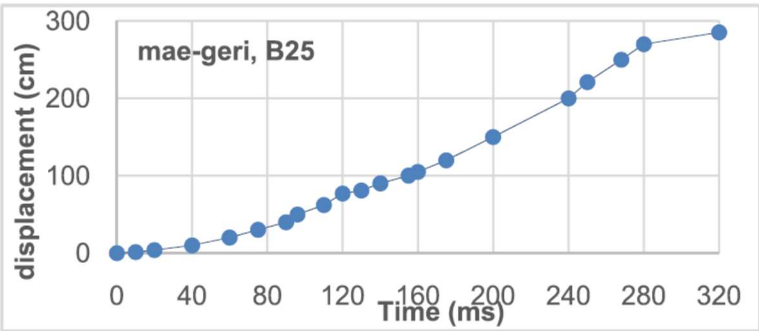

Fig. 10. Displacement of the foot projection, mae-geri, B25.

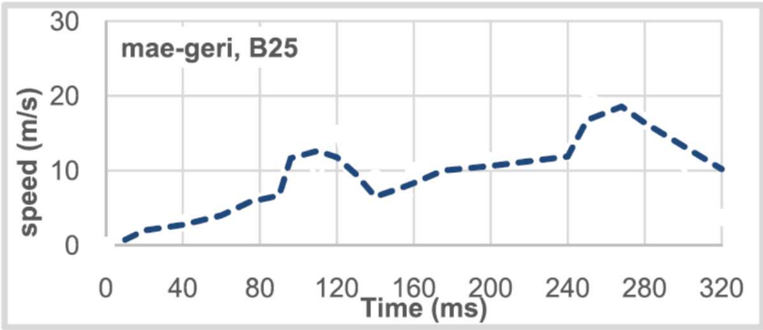

Fig. 11. Speed of the mae-geri kick, B25.

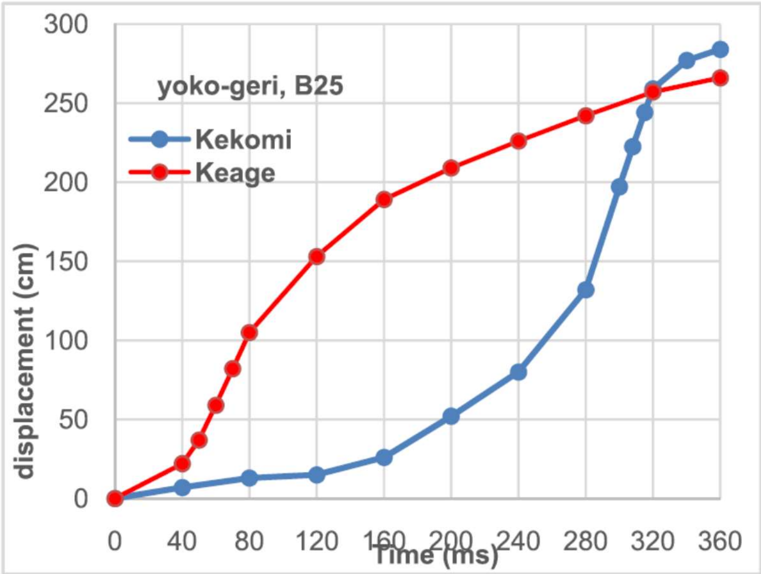

Fig. 12. Displacement of the foot projection, yoko-geri, B25.

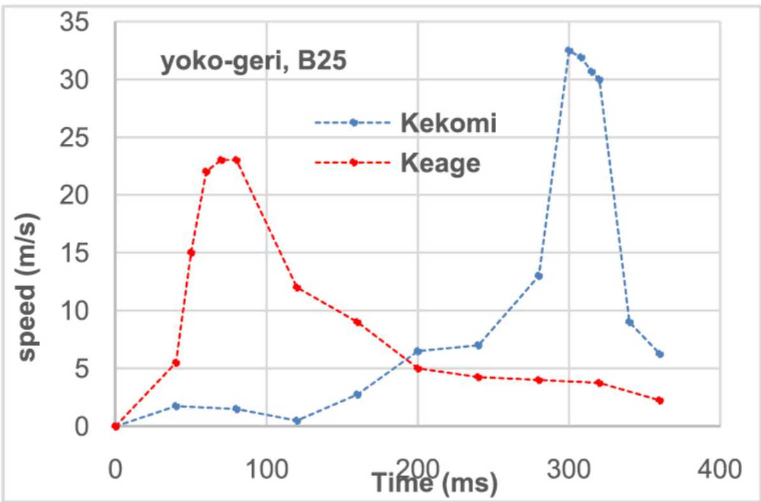

Fig. 13. Speed of the yoko-geri kick, B25.

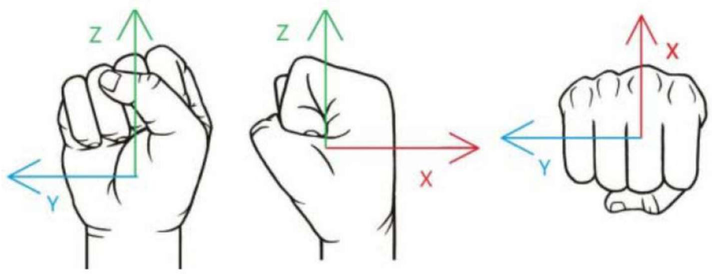

Fig. 14. Coordinates for the experimental tests (punch).

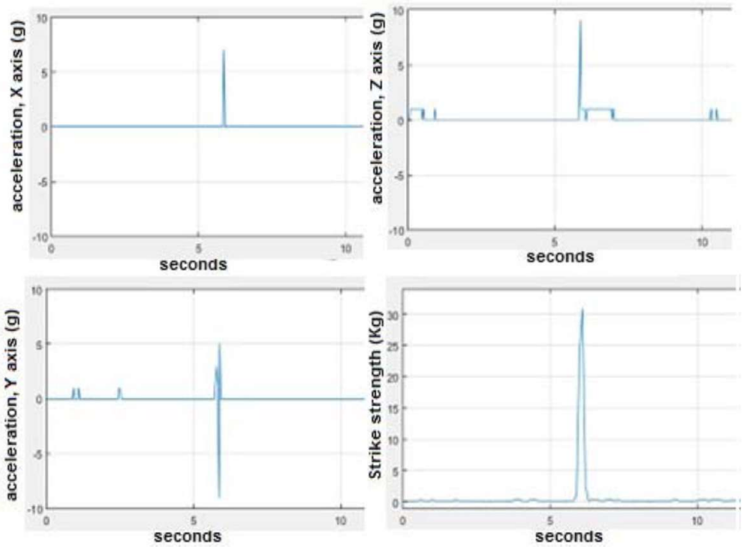

Fig. 15. Performance measurements of Athlete Y1.

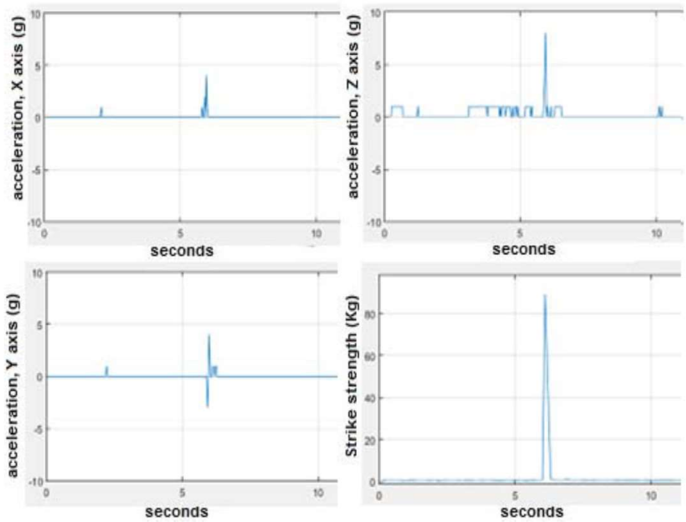

Fig. 16. Performance measurements of Athlete O2.

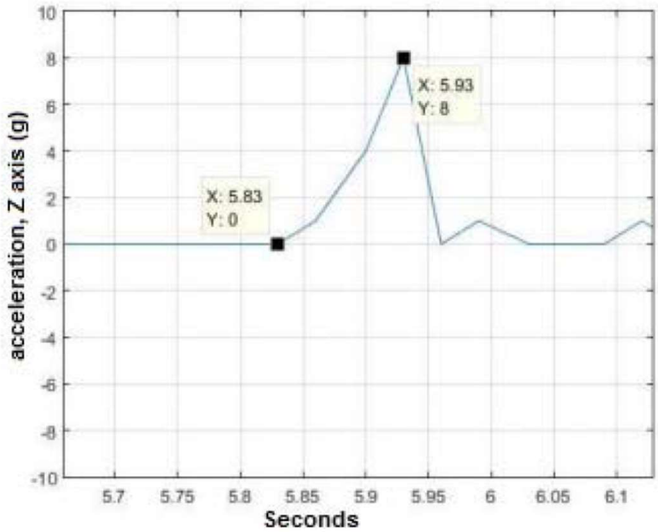

Fig. 17. Performance measurements of Athlete O2.

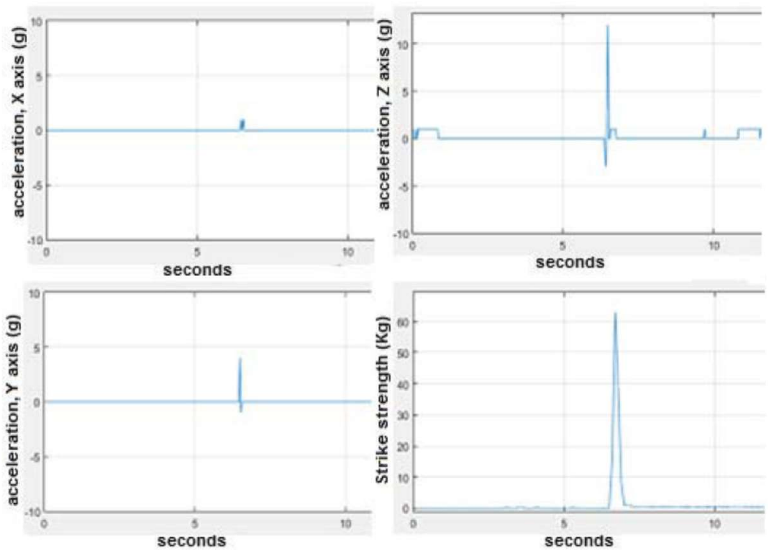

Fig. 18. Performance measurements of Athlete O3.

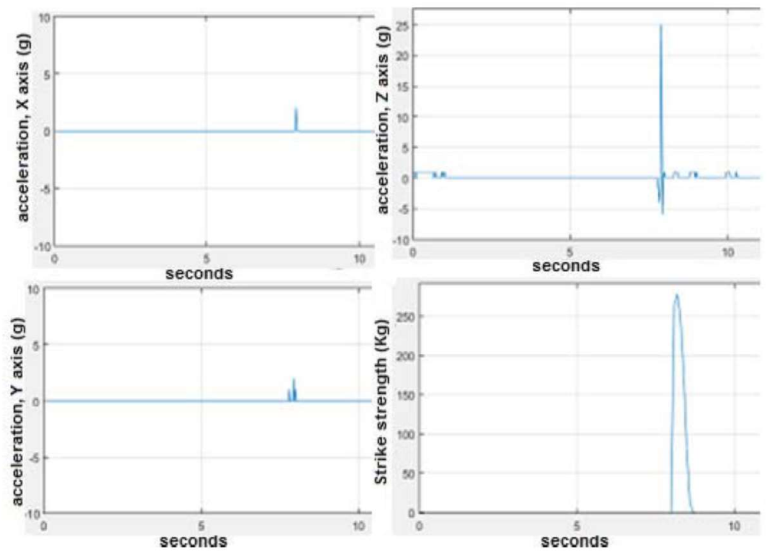

Fig. 19.

Performance measurements of Athlete B23.

B. Experimental Results

Fig. 5 shows the spatial displacement of the hand when the athlete B25, a black belt, male of 75 kg, is performing a fist gyaku-tsuki. The fist gyaku-tsuki is also known as reverse punch since it is a punch with the rear arm when stepping forward. In the gyaku-tsuki technique, the fist projection can be seen, with a good approximation, as a uniformly accelerated motion: in Fig. 6 the hand speed is growing, almost constantly, from 0 up to 12.5 m/s in the first phase of the movement (160 ms). After the peak, the speed is decreasing back toward zero in the second part of the movement (roughly 160 ms). The average acceleration is about 78 $m/^2$. These values are in line with measurements of the gyaku-tsuki movement proposed in the literature [24]. It is worth noting that in [24] a more complex system is used, based on video cameras plus off-line processing of the acquired images with a specific software. In Fig. 7, the same analysis of Fig. 6 has been repeated when the gyaku-tsuki movement is performed by athlete Br6, a brown belt, female of 60 kg. The waveform in Fig. 7 is similar to that in Fig. 6, but the maximum speed of the hand is almost halved, as well as the acceleration. This reduced dynamism of the gyaku-tsuki movement will result in a lower efficacy of the hits of athlete Br6 versus B25 [see also results in Table II(a)].

During the gyaku-tsuki movement, we also measured the angular speed of the pelvis, whose peak values are 16 and 12 rad/s for athletes B25 and Br6, respectively.

Figs. 8 and 9, for athlete B25, show the same measurements of Figs. 5 and 6, for the fist oi-tsuki, which is the punch with the lead arm (when stepping forward). From Fig. 9, the oi-tsuki is a sequential combination of three main parts. First, there is an almost uniform motion with a speed of about 2 m/s (rotation of the hip and forward step). Then (fist thrusts forward), there is an uniformly accelerated motion with a duration of about 150 ms, with a maximum speed of about 8 m/s. Finally, there is a deceleration phase of about 150 ms.

Figs. 10 and 11 show the displacement of the foot projection and the speed during a mae-geri, which is a front kick. From Figs. 10 and 11, it seems that initially the foot is moved with an accelerated motion (rotation of the hip) reaching a speed of about 13 m/s in 100 ms (acceleration of about 130 m/s^2). Then (lower leg movement), there is another accelerated motion at about 100 m/s^2 (from 130–270 ms). The final foot speed is about 20 m/s. Figs. 12 and 13 show the displacement of the foot projection and the speed of the yoko-geri movement, which is a side kick, and can be done according two different techniques: yoko-geri kekomi (blue lines in Figs. 12 and 13) and yoko-geri keage (red lines in Figs. 12 and 13).

For all the athletes in Table I, Table II(a) and (b) shows the maximum measured strength of a front punch strike and of a front kick strike during their training. Table II(a) and (b) shows also the ratio between these strengths and the weight of the athlete [kick-strength-to-weight ratio (KSWR) and punch-strength-to-weight ratio (PSWR)]. In addition, Table II(a) and (b) shows the feedback value (1: bad; 2: improvable; 3: good; and 4: excellent) of the system in terms of automatic evaluation of the athletes' movement when providing the shot. With respect to other biometric parameters, as in Figs. 5–13, or Figs. 15–19, KSWR and PSWR and the feedback value are useful as synthetic objective measures of the performed hit, and are easy-to-understand for nonprofessional athletes. Table II(a) and (b) refers to front punch strike and front kick strike just as an example. The same results can be obtained during a combat training match for all types of hits. The results of a series of multiple kicks or punches are stored separately in the instrument memory, while in real time, the display is refreshed to visualize the performance of the last hit.

For the reader's convenience, Fig. 14 remarks that a proper position of the accelerometer on the arm or leg produces the following:

1. positives Z accelerations when moving forward on the sagittal plane with parallel direction regarding the floor;
2. positives Y moving to the right of the subject on the transverse plane;
3. positives X moving up.

For example, Figs. 15–19 show the measured fist acceleration along the three axis (x, y, z), the execution time of the punch in seconds, and the strength (measured as the deformation revealed by the sensing node, type B, placed on the hit target). In Table II(a) and (b) and in Figs. 15, 16, 18, and 19, with the unit kg, we refer to kilogram-force, which corresponds to 9.81 N. The results in Fig. 15, measured during a test training of athlete Y1 in Table I, refer to a punch technique judged by the subjective coach analysis having a nonoptimal trajectory. In Fig. 15, a relevant ascending movement (X's spike up to 7 g), a quite large right-left oscillation and Z acceleration (i.e., in the target direction) can be noticed. This movement allows the athlete to produce a hit with a ratio versus its weight of about 0.5 for the punch. The test in Fig. 16 shows a better movement of the subject O2 in Table I (which indeed is an orange belt, with an experience twice that of athlete Y1). In Fig. 16, the acceleration along the direction of hit (axis z) is much higher than the other axis. The deformation of the target for the punch is equivalent to about 83 kg. The PSWR figure of merit is 0.82, roughly 60% better than the PSWR of athlete Y1, although much lower than the performance of the more experienced athletes in Figs. 18 and 19. The limits of the movements of the athlete O2 can be analyzed looking at the zoom of the z-axis acceleration in Fig. 17. In Fig. 17, the athlete O2 reaches a peak at 8 g with a transitory in less than 100 ms, of which 75 ms during the acceleration increase phase. The weak slope of the acceleration during the hit produces a strike with strength-to-weight ratio lower than 1.

Fig. 18 shows a trajectory, produced by athlete O3, evaluated as good by the coach and by our system. In Fig. 18, we can see the absence of ascending movement. There is a small deflection to the right of the subject, but the Z acceleration is good with a peak higher than 10 g. This leads to a fast hit and to a PSWR factor higher than 1 (1.22), 48.7% better than athlete O2. Fig. 19 shows a trajectory, evaluated as excellent by the coach and by the automatic evaluation system, taken by athlete B23. To be noted that in Fig. 19, there are no lateral or ascending oscillations. The forward acceleration in Fig. 19, along the axis z is remarkable, with a spike up to 25 g. The strength of the hit in Fig. 19 is higher than 250 kg with a PSWR of 3.63. Similar results are achieved for the Athletes B21 and B25. As a secondary comment, we remark that such good force result of the athletes B21, B23, and B25 are produced by the ability of use their legs to push against the floor ad use the hips and elbows to drive this energy directly into the strike without break this kinetic chain. Usually, an athlete manages such a coordinative skill around the tenth year of practice.

To achieve a feedback from the users, athletes, or coaches, they were asked to fill an evaluation questionnaire and to give an overall mark about the usefulness of the proposed system for training support (from 0, completely unuseful, to 5: absolutely useful; where 0–2 are considered negative marks and 3–5 are considered positive marks). Considering the overall testing population of 70 subjects, we achieved an average mark of 4.2 with 95.7% of positive marks, i.e., above or equal 3. The testing and evaluation campaign is still on-going to extend the subjects under test well beyond 70.

SECTION VII.

Conclusion

A system for athletes' performance measurements in combat sports has been presented. A low-cost implementation is proposed to address the market of nonprofessional athletes. It is organized as a distribute network of multiple wearable and battery-powered sensing nodes, with wireless BLE connectivity versus a gateway node that collects the biometric data. The gateway node also implements local tasks for signal processing and hit statistic evaluation, data storage, data visualization, and data transfer to remote hosts. Beside the analysis of waveforms related to different biometric parameters (e.g., speed, acceleration, spatial displacement, hit strength, and so on) the system also provides two intuitive parameters, KSWR and PSWR, and a synthetic value of the training effectiveness, to give an easy-to-understand feedback to athletes and coaches. By properly programming LUTs

at the gateway node side, the score for all hits can be weighted according to the effective traumatological damage they cause. The system is scalable in terms of sensing nodes, according to the specific combat sport. Experimental measurements on different athletes confirm the strong relationship between the device's tests and the real skill level of athletes, evaluated also through a coach subjective assessment.

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