exIMUs: an Experimental Inertial Measurement Unit for Shock and Impact Detection in Sport Applications

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Abstract. Wearable technology for physical activity recognition has emerged as one of the fastest growing research fields in recent years. A great variety of body-worn motion capture and tracking systems have been designed for a wide range of applications including medicine, health care, well-being, and gaming. In this paper we present an experimental inertial measurement system for physical impact analysis in sport-science applications. The presented system is a small cordless wearable device intended to track athletes physical activity during intensive workout sessions. The main distinctive feature of the system is its capability to detect and measure a wide range of shock intensities typical for many active sports, including martial arts, baseball, football, hockey, etc. Tracking of the sport specific irregular and fast movements is another important aspect addressed in the presented experimental system. In this paper we present the hardware-software architecture of the system and discuss preliminary in-field experimental results.

1 Introduction

Wearable computing systems for human motion tracking and physical activity recognition is a rapidly expanding field that is attracting a lot of attention from both academia and industry. Automatic human motion tracking facilitates the creation of new applications in a broad variety of domains, including human-computer interfaces, life care, wellness, sport, and gaming.

Over the past decade, various wearable motion capturing and gesture-posture recognition systems have been developed [1, 2, 3]. The integration into a single design of multiple sensors, such as triaxal MEMS accelerometers and gyroscopes, complemented with magneto and barometer sensors, has become a common practice in modern systems. In addition, recent advances made in MEMS and silicon technologies bring new a generation of miniature and low cost inertial sensors that provide high level of sensitivity, linearity, low noise level and high output data rate suitable for dynamic real time motion tracking applications. Existing motion tracking systems achieve a high level of accuracy when working either in a laboratory or when operated during very short execution time [1]. However, in real world scenarios, where various irregular motions and noisy background are present, the performance and accuracy of these systems might decrease dramatically [4]. How to achieve accurate and drift-free motion tracking, in terms of both hardware and software design, under real world conditions is therefore still an open research problem.

In this paper, we focus on Sport applications that are characterized in particular by strong physical impacts (shocks) and fast movements. The prime application domain for the presented system is the registration and tracking of *dynamic irregular movements*, such as boxing punches, baseball pitches, football kicks and volleyball hits. The main motivation behind of the presented system is to support a comprehensive analysis of the athletes performance by providing absolute values on the produced force, velocity and passed trajectory of the studied body segments. Such an analysis can provide a valuable feedback for athletes and objectively assess the individual's skills and techniques.

The main contribution of this paper is the exIMUs platform, an Experimental Inertial Measurement Unit for Sport applications. The exIMUs system is a single small wireless device designed to be worn on the studied body segments, including for instance the fist, ankle or head. The presented system consists of a full nine Degrees of Freedom (DoF) inertial sensors technology, including a triaxial acceleration sensor able to register high shocks (up to $\pm 400g$). A low-energy Bluetooth wireless transceiver is integrated in exIMUs for data communication with a host machine.On the software side, an Extended Kalman Filter based sensor data fusion algorithm [5, 6] has been developed for motion tracking and velocity analysis. Preliminary in-field experiments have been run to verify the system functionality and collect an initial set of comprehensive data. The experimental setup was complemented with a high rate multi-camera visual analysis system in order to obtain ground truth data for accurate sensor calibration and to refine the tracking algorithms.

This paper is structured as follows. In Section 2 we overview mainstream motion capture and tracking technologies developed for various applications. Section 3 discusses the details of the exIMUs system architecture and the core hardware-software components. In Section 4 we present experimental results obtained in a real test case environment. Finally we conclude the paper in Section 5 with summary and future work discussion.

2 Related work

Existing body-worn Inertial Measurement Unit (IMU) sensor systems for physical activity recognition vary in target applications, purposes, usage scenarios and final outputs. Visual analysis, traditionally, is the most popular method for human biomechanics analysis, and has been used in sport-science and sport medicine labs for years [7, 8]. However, recently appeared MEMS sensor technology is able to complement and even replace traditional systems with equally accurate, and yet more flexible, personal and low cost solutions [9, 10, 11]. Ermes et al. [12] present a study on detection of both daily and sport activities in a real-life, non-laboratory environment. Two wearable acceleration sensors placed on the subject's hip and wrist were utilized to analyze actions such as cycling, playing football, exercising with a rowing machine, and running. A hybrid decision tree classification method was designed to recognize and classify different actions. Long et al. [13] present a single-sensor acceleration-based body worn system for computing daily energy expenditure in sportive activities such as soccer, volleyball, badminton and table tennis. This study compares a Bayesian classification method with the Decision Tree based approach. The results show a similar classification accuracy for both methods approximately equal to 80%. Mitchell et al. [14] propose a framework for automatic classification of sporting activities using the embedded accelerometer found in modern smartphones. Three classification approaches were investigated: a Support Vector Machine (SVM) approach, an optimized classification model and a fusion of classifiers to recognize soccer and hockey activities. Recognition accuracy of 87% was achieved using a fusion of classifiers, which was 6% better than a single classifier model and 23% better than a standard SVM approach [14]. IMU Arrays [15] introduced by Berkson are IMU-based systems designed for quantitative biomechanical analysis of baseball pitching. The system consists of a set of MEMS acceleration sensors placed on the chest, upper arm, forearm, and hand to allow independent measurements of each arm segment. The study shows general applicability, high level of accuracy and advantages of the presented system over traditional visual motion-tracking analysis.

Detection and analysis of motion sequences in martial arts is another popular application of wearable IMU systems. Motion sequences in combat and martial art sports are, typically, characterized by irregular and fast types of movements, that greatly complicate automatic recognition and limbs tracking. Heinz et al. [16] present an experimental work on real-time recognition of Kung Fu motion sequences using wearable sensors. The system contains a set of body-worn acceleration and gyro sensors for action detection. The tree-based classification algorithm was chosen for action recognition. The results confirmed feasibility of the task to automatically recognize movements in real time. Analysis of boxing punches using 3D gyro sensor was introduced by Morita et al. [17]. In this study, the authors discriminate different types of punches based on the angular velocity of the subject wrist measured by the gyro sensor.

Along with comprehensive motion, biomechanical analysis, detection and quantitative study of force (shock) is the subject of interest and research in many active sports, especially martial arts, baseball, football, and sport-medicine applications. Such an analysis has many applications in training and rehabilitation, assessment of individual physical conditions and techniques, as well as objective judgment and points scoring during competitions [18]. Traditionally, piezoelectric sensors and pressure transducers inserted under the target surface (punching bag, force plate, shoes) have been used as the major technology in this field [19]. In general, these systems provide an accurate measurement of static and dynamic pressures applied on the target object. However, traditional approaches have some critical drawbacks such as high cost, special setup, extensive calibration and large dimensions, making them only available for elite athletes in special sport medical labs. Modern market available MEMS accelerometers are able to tolerate and register high level of dynamic shocks (up to 10000g and 400g respectively) produced by any physical impact during sportive actions (throwing, kicking, jumping, punching, etc). This, in turn, opens the possibility to complement and extend traditional human biomechanical analysis systems with force reporting facilities. However, due to the novelty of the technology and topic, there are only few scientific works available on this subject.

Walilko et al. [20] evaluated the punch of experienced amateur boxers to assess head impact responses and the risk of injury. Each boxer was instructed to strike a headform with a left hook or left jab. The headform was instrumented with MEMS accelerometers to determine the translational and rotational acceleration, and neck responses. The force impacts on the jaw region of the headform were measured using pressure sensor. High speed video recorded each blow and was used to determine punch velocity. Equilibrium was used to determine punch force, energy transfer, and power. The study showed strong correlation between pre-impact motion and post-impact shock.

In the field of force detection in martial art sports, several independent research [21, 18] and many hobbyist projects were implemented. They all utilize similar technology by equipping punching bags or force plates with MEMS acceleration sensors to register geometrical inclination of the object after the impact. This, in turn, allows simple physics equations to be applied to compute force with known parameters of pendulum length and mass of the object.

The system presented in this paper improves on the above approaches in two ways. In the first place, unlike other body worn sensors, we aim to detect, classify and quantify *irregular* and *fast* movements, such as shocks, characterized by an extremely *wide range* of sensory values. While target mounted sensors are able to support these applications, as discussed above, our system is designed to be worn by the athlete on the body segment of interest. This extends the approach to those cases where no target is present, and provides critical data regarding the motion before and after a shock. On the other hand, a wearable approach raises certain issues and challenges in accurately measuring and quantifying the produced shock. To the best of our knowledge, however, there are no existing studies on this kind of approach.

3 System design

The exIMUs system is an experimental inertial measurement unit designed specifically for sport-science applications. The main distinctive feature of the presented system is its capability to detect high level of shock (acceleration history) produced by any sportive actions such as punches, kicks and swings.

3.1 Hardware architecture

Below we overview the implementation details of the exIMUs system focusing on its architecture and hardware details. The guiding requirements in designing wearable systems like exIMUs include real-time and accurate detection of motion series, weight and size constraints, wearable comfort, wireless communication capabilities and low power consumption. Additionally, due to our specific application scenarios, the physical reliability and damage tolerance after multiple shocks is another important aspect to be addressed in the design. Power consumption requirements determine the choice of low power hardware parts and system sleep-active scheduled operations.

The block diagram of exIMUs is presented on Figure 1. It consists of a wearable sensor device, a wireless communication interface, and the host side processing that includes software analysis and visualization. A key component of our design consists of an appropriate and market available MEMS accelerometer whose sensitivity must span the entire range of all possible accelerations in the sports of interest. Based on the available information on the maximum level of shock and acceleration of $\pm$ 80g [19, 20] measured during sport-medical experiments, we selected the newly introduced STMicroelectronics (STM) H3LIS331DL MEMS sensor. It provides 3-axis acceleration measurements with selectable range from ± 100 up to ± 400g with noise density of 15 mg/$\sqrt{Hz}$ for ± 100g range. Additional features of the selected sensor chip include a serial interface, several low power modes and small PCB foot print. However, during our first lab experiments we revealed that the level of noise of this sensor during stationary position was about ± 1.2g in magnitude, which would prevent us from performing any accurate motion analysis. We have therefore introduced an additional low-range, 3-axis acceleration sensor LIS331HH with high sensitivity ± 0.07g and low noise density 0.6 mg/$\sqrt{Hz}$ in the range of ± 6g, in order to complement the high-range sensor. Thus, two inertial acceleration sensors are used in our system: shocks and the pre-post impact phases of movements are detected by H3LIS331DL, while the relatively slow and medium actions (below ± 6g) are sensed by LIS331HH. For angular rate detection we have selected the STM MEMS gyroscope L3G4200D which provides ± 2000dps measurement range with 0.03 dps/$\sqrt{Hz}$ noise density. Moreover, a 3-axis magneto sensor MAG3110 has been included on the board in order to correct the gyro drift along the Z axis (yaw rotation). In the final design, all four sensors have been placed on the board and connected to the common serial I2C line. The access reading time for all four sensors combined is equal to 2.1 ms (24 bytes of raw data in a burst packet reading mode on I2C interface). This was one of the limiting factors in selecting the sensor sampling rate. Restrictions of the blocking communication API [22] also constrain the sampling rate by similar amount. Thus, all MEMS sensors are sampled at a constant rate of 200Hz while the magneto sensor is sampled at 80Hz, the maximum rate for the selected magneto sensor.

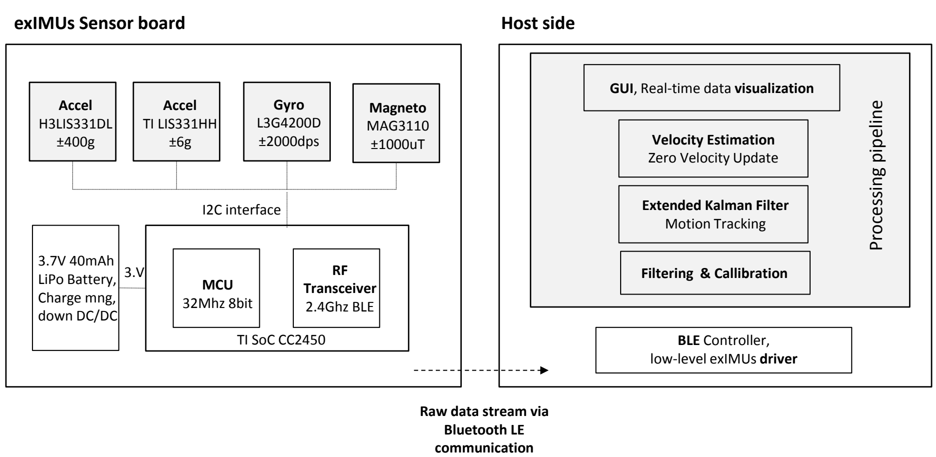

Fig. 1: exIMUs block diagram

On-board operations control, sensor sampling and RF operations are all handled by the Texas Instruments (TI) SoC CC2540 that combines a 32MHz low power 8-bit microcontroller and a Bluetooth Low Energy (BLE) transceiver. The embedded application code is written in C and runs on top of the TI Operating System Abstraction Layer (OSAL) API. Communication operations are handled by TI's BLE Protocol stack [22], which provides a software interface to all BLE services including protocol configuration, devices and profiles discovery, and data transmission and reception. The power supply chain of the exIMUs board contains a 3.0 Volt step-down DC/DC converter, a battery charge management controller and a 3.7V LiPo accumulator with a 40mAh capacity. Although the relatively small capacity of the battery guarantees only about one hour of continuous operation, its limited size and weight are ideal to make our system unobtrusive. The peak power consumption measured during experiments was equal to 41 mA (all components are in active states). The current drawn in standby mode was measured at a level of 0.3 mA. The exIMUs sensor board with the attached battery is shown on Figure 2. The complete and assembled system is placed in a plastic enclosure with velcro strips for limb mounting. The size of the final system is 30mm(W) x 60mm(L) x 22mm(H) and 40 grams in weight.

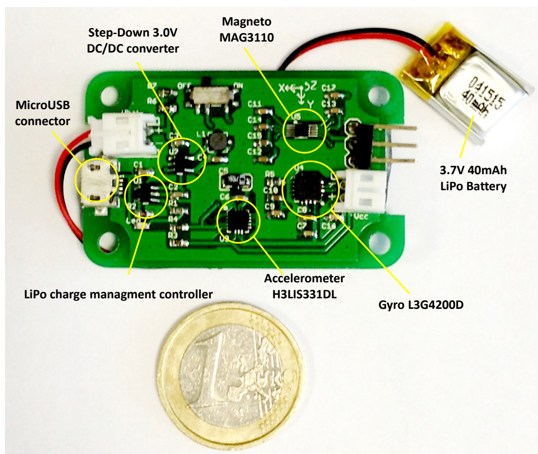

Fig. 2: exIMUs sensor board.

3.2 Data processing

Due to the limited processing capability of the on-board MCU, all the software data analysis on the raw sensor readings, including calibration, filtering, sensor data fusion and motion recognition algorithms, conducted on the host side, on a BLE enabled PC. The host consists of a built-in BLE controller, a set of custom developed exIMUs drivers, the core software algorithms and a front-end GUI. The SW processing part consists of calibration, filtering and motion tracking modules. The latter, in turn, includes a sensor data fusion algorithm based on the Extended Kalman Filter method.

The first software module in the processing pipeline is a low level driver that handles exIMUs ad-hoc service commands and delivers a stream of formatted raw sensor data from a built-in (or USB plugged) Bluetooth LE controller to the higher level application modules. Low-pass filtering operations are further applied on the acceleration and gyro signals in order to reduce the background sensor noise. The filtered data is then forwarded to the calibration module, which performs the offset calculation for the gyro and acceleration sensors. In stationary position, 256 samples are gathered to calculate the gyro mean bias from the zero level on each axis. Moreover, the magneto sensor is calibrated separately in order to cancel hard and soft iron effects. This operation is performed for each cold start of the sensor board.

Next, the filtered and calibrated data stream is fed into the sensor data fusion module, the heart of the entire processing pipeline. This part implements a quaternion based Extended Kalman Filter method [6, 23] - a recursive algorithm that estimates the system state (state vector) and the state error covariance matrix from the acquired sensor measurements (two accelerometers, one gyroscope and magnetometer 3 axis each) and the known nonlinear system state transition dynamic model together with sensors measurement noise statistics. The quaternion representation provides a number of advantages over Euler angles including Gimbal lock-free representation, plain normalization and computation instead of complex trigonometry. The estimated state vector x contains an orientation quaternion q_0^b, angular velocity ω_0^b and low frequency gyro drift δ for in-line calibration:

$$x = \begin{bmatrix} q_0^b \; \omega_0^b \; \delta \end{bmatrix}^T \tag{1}$$

In the current implementation we use a non-variable measurement error covariance matrix, assuming white Gaussian noise in all sensor measurements. We also assume that the measurement errors are independent of previous states and perturbations.

The direction cosine matrix (DCM) in quaternion representation is given by the following equation as discussed in [6]:

$$C_0^b(q) = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1 q_2 + q_0 q_3) & 2(q_1 q_3 - q_0 q_2) \\ 2(q_1 q_2 - q_0 q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2 q_3 + q_0 q_1) \\ 2(q_1 q_3 + q_0 q_2) & 2(q_2 q_3 - q_0 q_4) & q_0^2 - q_1^2 - q_2^2 + q_0^2 \end{bmatrix} \tag{2}$$

where quaternion q_0^b is given as $\begin{bmatrix} q_0 \; q_1 \; q_2 \; q_3 \end{bmatrix}^T$.

The state transition matrix that represents quaternion transformation from body frame o to the global frame b, q_0^b is propagated according to the differential equation:

$$q_0^b = 1/2[\Omega_o^b]q_0^b \tag{3}$$

where $\Omega_o^b = \begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix}^T$ and $\omega_o^b = \begin{bmatrix} \omega_x \; \omega_y \; \omega_z \end{bmatrix}^T$

The propagation of the rate gyro drift error defined in [23], δ, is determined prior to operation by static testing. The error propagates as:

$$\delta = \begin{bmatrix} 1/\tau_\delta & . & . \\ . & 1/\tau_\delta & . \\ . & . & 1/\tau_\delta \end{bmatrix} + w_\delta \tag{4}$$

The measurements from the exIMUs board are given as a measurement vector that consists of acceleration, rate gyro and magnetometer triads:

$$z = \begin{bmatrix} f_{imu} \; \omega_{imu} \; h_{imu} \end{bmatrix}^T \tag{5}$$

The accelerometer measurements for the EKF are modeled as the gravitational force complemented with a stochastic error vector $\bigtriangledown_{ac}$ as defined in [23]. Using the quaternion representation to rotate the constant gravitational force, the accelerometers measure:

$$f_{imu} \simeq C_0^b(q) \begin{bmatrix} 0 \\ 0 \\ -\|g\| \end{bmatrix} + \bigtriangledown_{ac} = \|g\| \begin{bmatrix} 2(q_0q_2 - q_1q_3) \\ -2(q_0q_1 + q_2q_3) \\ -q_0^2 + q_1^2 + q_2^2 - q_3^2 \end{bmatrix} + \bigtriangledown_{ac} \tag{6}$$

This equation for orientation estimation is only valid when the magnitude of the measured acceleration vector does not exceed gravitational level, $\pm 9.8 m^2/s$. In our application, however, the range of measured accelerations is far above gravitational e.g., when the motion or physical impact are taking place, which will be shown in the next section. In such cases the presented sensor fusion algorithm relies only on the gyro and magnetometer measurements for the orientation estimation during active motions. As soon as the magnitude of the sensed acceleration signal on all 3 axes combined returns to the gravitational level the EKF module corrects the orientation with accelerometer measures.

The sensed gyro angular rate ω_{imu} does not depend on the gravitation force and is modeled as direct measurement of the corresponding EKF state in addition to the gyro drift error, δ, and stochastic error vector ϵ,

$$\omega_{imu} = \omega_o^b + \delta + \epsilon \tag{7}$$

The sensed magnetic field is modeled as magnetometer measurement vector transformed into the body frame DCM quaternion representation complemented with a stochastic error vector $\bigtriangledown_{mag}$,

$$h_{imu} \simeq C_0^b(q) \begin{bmatrix} h_x \; h_y \; h_z \end{bmatrix}^T + \bigtriangledown_{mag} \tag{8}$$

The orientation of the gravity vector obtained in the sensor fusion module is used for the consecutive velocity estimation module. The estimation of linear velocity is calculated by subtracting the estimated gravity vector from the acceleration signal, measured either by the low or the high range acceleration sensors, and the successive integration of obtained values. To reduce the integration accumulation error, we utilize the in-line zero velocity update (ZUPT) technique [24] to reset the instantaneous velocity to the initial zero state. The motion phases recognition module implements a heuristic state machine that breaks down any movement into acceleration, impact, deceleration and steady states. ZUPT takes place when the exIMUs device is recognized to be in the steady state and no motion is happening.

3.3 Force detection

Each triad of recognized acceleration, impact and deceleration states is an input for the successive force analysis module. According to Newton's laws, the quantitative force analysis with established acceleration is only possible when the mass of a collided object, in our case a studied limp on which exIUMs is mounted on, is constant and known. But this is not always the case for many sportive actions, like a boxing punch or a football kick. In such movements, the effective mass of the limb is combined with the partial mass of the body torso, which is difficult to measure directly. For these cases, in our method we introduce a lookup table-based approach that establishes the correspondence between the measured acceleration history, pre- and post-impact time, and a verified reference force values. The reference force data is obtained during an initial calibration step by measuring the physical impact by means of external (not wearable) dedicated force-pressure sensors mounted on a target object.

4 Experiments

Multiple pilot experiments were conducted to verify whether the exIMUs system is capable of picking up all relevant details of sportive actions performed in real life conditions. Currently the motion tracking and recognition modules are under development an evaluation. Two in-field experiments with exIMUs were performed to study football and boxing actions. The main objective of these experiments was to evaluate the on-board hardware parts and their settings, including sensors sensitivity and ranges, the selected sample rates, latency and sensors noise statistics. Additionally, the utilized Bluetooth low energy transceiver was evaluated with respect to the data throughput and maximum communication range. The host side processing pipeline included filtering, calibration, visualization and the data logging module for subsequent post processing analysis. All studies were complemented with camera-based motion analysis. The experimental setup included three high rate cameras (GoPro Black Edition with 240 fps at 848x480 pixel resolution) placed at different locations in the experimental scene. High contrast markers were placed on top of the exIMUs device to facilitate accurate visual tracking. The results obtained form the visual system, including velocity and displacement, are used as ground truth data for inertial motion tracking and as a reference to verify the EKF module output.

In the first experiment we studied football kicks performed by an amateur middle weight (80kg) athlete with a standard size ball. The sensor device was fixed on the lower part of the subject shin. After the sensor calibration procedure, the athlete was instructed to perform a series of direct kicks with maximum force. A sample of the obtained sensor results is presented on Figure 3. In accordance to the hardware architecture, the low range acceleration signal (top right graph) is clipped at the level of $\pm$ 6g. The maximum levels of the registered acceleration and rotational velocity were equal to 57g and 1800deg/sec, respectively. The average impact time with the ball was equal to 60 ms, while the pre-impact acceleration time registered for all performed kicks was in a range of 300 to 460 ms.

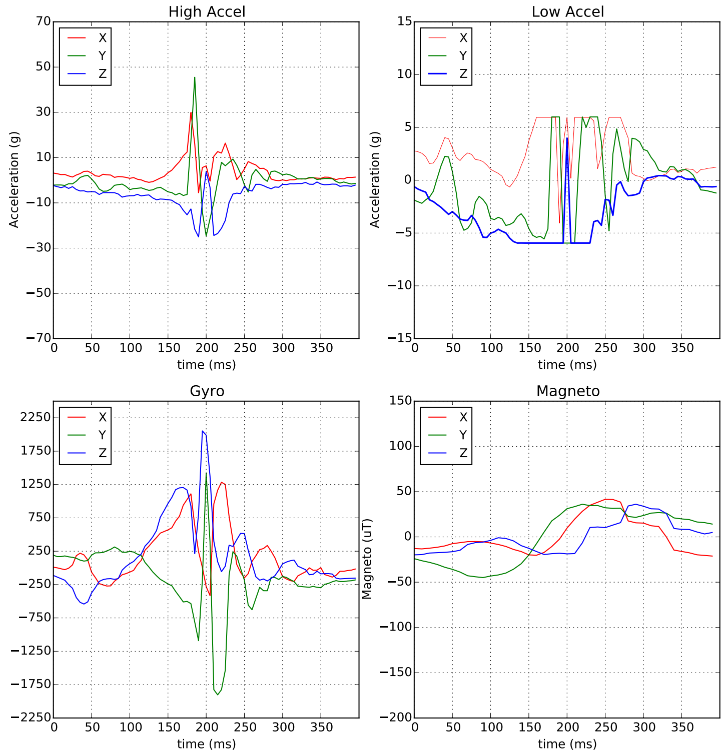

Fig. 3: Football kick sample example.

The Bluetooth LE communication range measured during this study (outdoor environment) was equal to 18 meters at a -6 dBm output power setting, and 26 meters at 0 dBm. However, communication was still possible at greater distances but this led to packet losses. Data latency from the remote sensor board to the host side logging system was on average equal to 40 ms.

The second experiment was intended to evaluate boxing striking techniques of two experienced amateur boxers. The weight of the athletes was 71 and 80 kg, respectively, that represented two different weight divisions. Certified 10oz size gloves were used to perform two series of direct (cross punch) and rotational punches (right hook) with the maximum possible force and speed. A heavy punching bag with weight of 45 Kg was used as a target object. The exIMUs device was placed on the athletes leading hand wrist. In order to increase fixation and minimize sliding effect during punch impact, the device was covered by the glove velcro strap. Figure 4 and Figure 5 respectively present samples obtained for both kind of punching techniques for 80 kg athlete.

The analysis of the obtained inertial information revealed that the straight punches produce a higher shock impact of approximately 80g in magnitude, as opposed to the hooks which produce an impact of 65g. Both athletes in our experiments showed similar

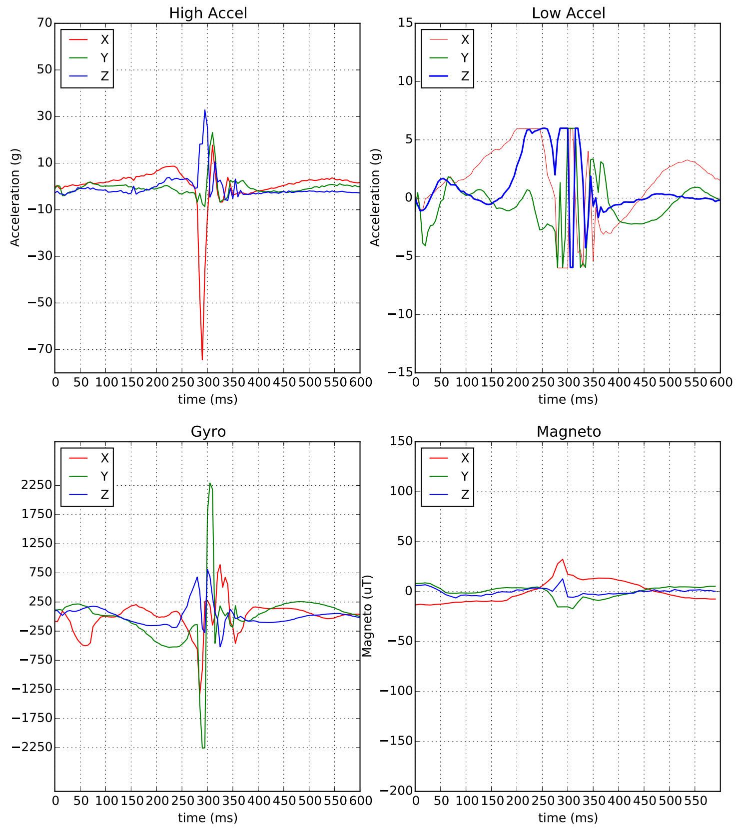

Fig. 4: Direct punch sensors samples.

pre-impact acceleration dynamics for straight (200ms) and rotational punches (300ms). However, pick shock acceleration was slightly higher for the heavier athlete (78g max against 69g for lighter). These values are aligned with previously published results [20] on boxing punches hand dynamics. This study reports maximum impact shock for direct punch registered at the 80g level with pre-impact time at 330 ms.

The total impact time for hooks was longer than the time registered for straight punches, for a total of 25ms and 15ms respectively. The rotational velocity registered for hook punches was equal approximately to 1500 dps that is aligned with results presented in [20]. It reports a maximum 1700 dps rotational rate for punches. Finally in our study, the maximum detected level of rotational velocity for direct punches exceeded the threshold of 2000 deg/sec along the Y axis at the moment of impact, the maximum measurement range of the utilized gyroscope. This can be explained by the high acceleration magnitude of 80g and the very short impact time of 15 ms that produced a very fast twist of the device along the Y axis at the moment of contact with the punching bag. This led us to the conclusion that the chosen gyroscope is not capable to com-

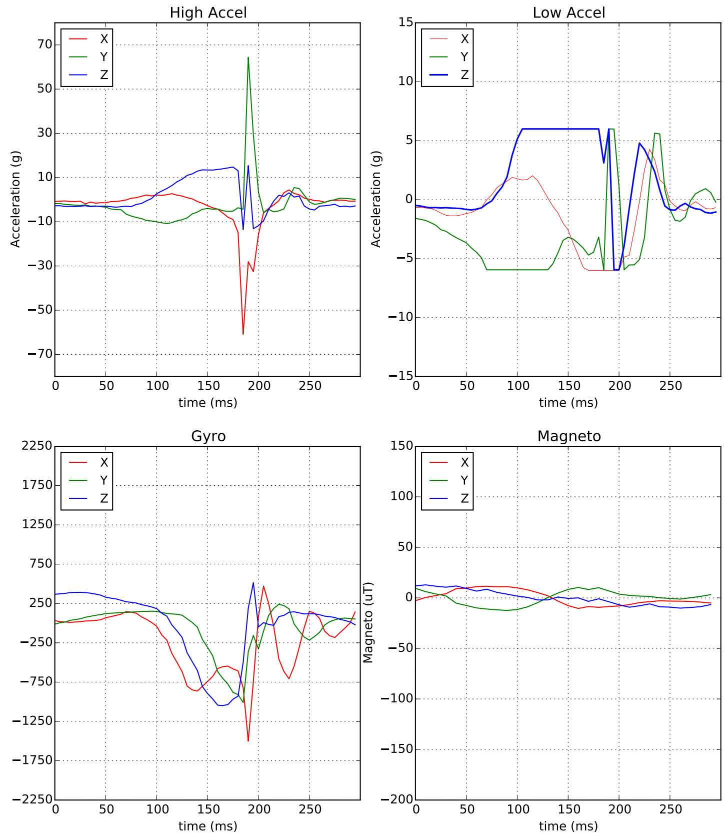

Fig. 5: Rotational punch sensors samples.

pletely cover the whole range of possible rotational velocities in sport. As an example, the maximum level of rotational rate reported for baseball pitch experiment [15] was equal to 2500 deg/sec.

5 Conclusion

In this paper, we presented a wearable inertial measurement system, exIMUs, for human biomechanical analysis in sport-science and sport-medical applications. The system consist of a set of cutting-edge triaxal MEMS and magneto sensors that support capturing motion in 9 DoF. The main distinguishing feature of exIMUs is the use of a high range acceleration sensor for registration and analysis of high level physical impacts and shocks produced by various sportive actions. The details on the exIMUs system hardware architecture and software processing pipeline have been presented.

Two proof-of-concept, in-field experiments on football and boxing techniques have been conducted in order to verify the sensor platform performance in real life conditions. The analysis of the obtained timing and inertial information shows their strong consistency with previously reported studies. However, the experiments have revealed certain limitations in terms of sensitivity range of the chosen gyroscope sensor. In spite of that, our experiments proved the general applicability of the presented system for biomechanical analysis in sport that might provide valuable information for athletes and coaches in related sports. Moreover, the presented sensor system and analysis might be applied also to other sports such as golf, tennis and volleyball, among others, where fast and strong movements constitute the main part of the performance.

Future developments on the exIMUs system includes a thorough evaluation and verification of the EKF algorithm using the reference values obtained from visual analysis, as well as further refinement of the sensor data fusion, motion recognition, and quantitative force measurement modules. Along with the software algorithms, our future work includes a revision of the hardware platform. For instance, the sensors sampling rate can be increased by improving the platform performance for an even more accurate and fine grained detection of physical actions. More compact and light weight platforms can be constructed for more comfortable usage. Finally, we are studying the feasibility of a complete onboard motion processing run on a separate ARM-based MCU, which would eliminate the need of continuous RF streaming to the host and allow the battery life to be considerably extended. For the energy-performance optimization of the ARM-based sensing platform we utilize a model-driven design approach supported by simulation environment presented in [25].

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