

# A Wearable Inertial Sensor Unit for Jump Diagnosis in Multiple Athletes

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## 1 OBJECTIVES

Flight and stance duration during jumping represent basic and very useful information for track and field coaches, and empirical evidence has been given that these parameters correlate strongly with elite performance (Hunter, 2004; Li et al. 2010; Slawinski et al. 2010). In highly dynamical sports such as track and field, athletes must be able to generate high forces within a very short time and in an appropriate manner. Consequently, reactive strength training including multiple jumps or drop jumps from different heights is very important for such athletes (Kale et al., 2009, Markovic et al., 2007). Objective feedback on performance is crucial to ensure a high quality of such a training as intrinsic information is merely available to the athlete due to the high movement velocities. From a trainer's perspective, on the other hand, the quality of performance cannot be assessed precisely enough by pure observation.

For the diagnosis of jumping performance in field-based conditions, several devices have been established in the last years. Contact mats or optoelectrical systems like Optojump® allow a precise and unobtrusive measuring of temporal parameters, but limitations must be stated according to the operational area as well as group or ubiquitous monitoring. More recently, the availability of miniature solid-state inertial measurement units (IMUs) offers large opportunities to overcome these restrictions, and therefore open a new perspective for in-field diagnosis. Combined with wireless data transmission, IMUs can be used to provide athletes and coaches with fast and accurate performance measurements to improve athletic development and elite performance. Additionally, IMUs merely affect athletes during performance due to their small size and weight.

IMUs have already been used to detect kinematic parameters in track and field applications. High correlations could be shown between IMUs and

reference measurements (force platforms and optometric systems) for flight time and jump height during counter-movement-jumps (Picerno et al. 2011;  $r=.87$ ) and for reactive strength index during drop jumps (Patterson and Caulfield, 2010;  $r=.98$ ). Reactive strength index, for example, can be used for several purposes for the optimization of plyometric training or for injury prevention (Mc Clymont, 2003). It has also been applied as a tool to judge athletes' recovery state (Horita et al. 1999; Toumi et al. 2006).

Bergamini et al. (2012) reported mean differences of .005 seconds between IMU and high-frequency video or dynamometry for stance and stride durations during sprinting. Lower correlations between force and acceleration peaks for drop jumps ( $r=.70$ ) and countermovement jumps ( $r=.55-59$ ) were found if only a three-axis accelerometer data were considered (Tran et al. 2010).

The aim of the recent study was the development and validation of an inertial sensor based device for detecting explosive jump events in elite athletes. Additionally, an ubiquitous group monitoring should be supported to use the device during training sessions with multiple athletes.

## 2 METHODS

### 2.1 System Design

A flexible wearable inertial sensor unit was developed, that should support easy adaptation to different diagnosis scenarios without changing the hardware. Main requirements were a high data resolution and accuracy, a direct connection to smart phones/tablets without additional hardware, a logging of raw data as well as compactness, little weight, easy usability and long battery lifetime.

To connect the sensor unit with mobile devices, a Bluetooth Low Energy (BLE) connection was

chosen. It allows ranges in free field up to 30m. In comparison to classic Bluetooth or WiFi, BLE can save up to 100x more energy. A drawback is smaller amount of data that can be transferred in time. This is compensated by an on-board processing. All sensor values are direct handled by the MCU. Only the results (e.g. stance duration) are sent. Additionally, all raw data is saved on an internal microSD card for later PC analysis. Via microUSB data can be read out and battery recharged.

To ensure an easy usage of the system, an Android App was developed. It connects to the sensor units of the athletes automatically. A sensor unit itself wakes up itself, so that no switch is needed. As soon as for example a jump was detected, the data is processed by the MCU, sent via BLE to the App and the results are displayed there (see Figure 1). Trainers can select one or more sensor units in parallel to monitor different athletics at the same time.

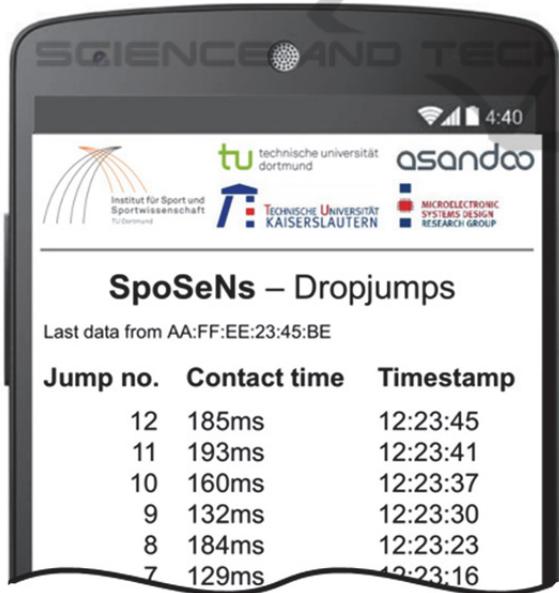


Figure 1: Screenshot of Android App.

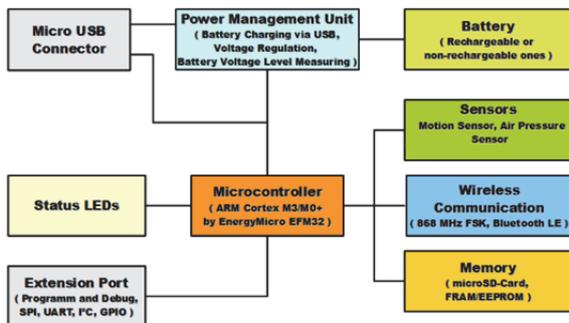


Figure 2: Sensor unit hardware overview.

Be capable of using the system for future scenarios, a platform-based approach was chosen. A board including MCU, sensors, wireless communication, memory, power management unit, and extension port was developed. Depending on the scenario, it can be equipped with the components needed for it.

For on-board processing of data and system management the world most energy efficient ARM Cortex M3 processor Giant Gecko from Silicon Labs was chosen (48MHZ, 1MB Flash, 128KB RAM).

Two sensors can be used: the IMU MPU-9150 from InvenSense combines a 3-axis accelerometer (up to 1 kHz and +/-16g), 3-axis gyroscope (up to 1 kHz and 1000 deg./s.) and 3-axis magnet field (about 100Hz) sensor in one chip. Additionally in the future, an air pressure sensor can be mounted capable measuring height differences up to 10cm.

For BLE communication, the Nordic nRF8001 is used (up to 30m free field). An own antenna was designed for optimal electromagnetic radiation. A second radio working in sub-GHz band can be used for future scenarios to enhance range (up to 200m free field).

An internal microSD card can save data up to 4GB.

The power management unit handles different power sources (normal battery, rechargeable battery, USB power) and recharges batteries. Batteries last for several hours.

An extension port can be used for future add-ons like new sensors. Figure 2: Sensor unit hardware overview gives an overview.

Overall size of the unit is 80x56x24mm<sup>3</sup> (see Figure 3).



Figure 3: Sensor unit (left) and board (right).

For fast software development and fast testing of new algorithms a software framework following a layered approach was created. Each layer abstracts from the layer below. Accordingly, parts or layers of the software can be changed easily without modifying any other component. For example, sensors can be changed or added without touching the other parts of the software. Basic tasks like initializing the MCU or the basic operating system are abstracted from the application itself (see also Figure 4).

The lowest layer connects to the hardware interfaces. The “device drivers” layer handles all low level hardware like wireless radios or getting sensor data. The layer “user libraries” provides basic functionalities to the application. The “Task manager” for example allow parallelization of jobs like getting sensor data, saving it in raw format, processing it, and sending it via BLE. The “BLE” module abstracts from the BLE hardware and provides for example easy access for sending “advertisement data”, which can be read by the App. The “Motion” module does pre-processing of the IMU data and provides the information to the next layer.

In “user program” the main part of the application is written (here “Dropjump”). It utilizes and combines functionalities of the lower layers without interfering with the layer itself. All modules are compiled and linked together to get at the end the final software for the sensor unit. This way, new applications can be developed in short time and parts of the hardware can be extended or replaced, respectively.

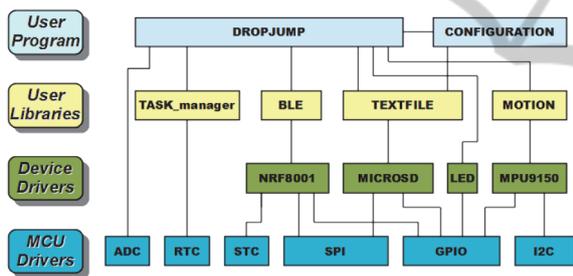


Figure 4: Sensor unit software overview.

## 2.2 Evaluation Study

The purpose of the evaluation study was first to identify recognizable features in the data signals supplied by the IMU for the estimation of stance ( $t_s$ ) and flight duration ( $t_f$ ) as well as jump height ( $H$ ) and reactive strength index (RI). Stance duration was determined by the first (landing) and last (takeoff) ground contact of the feet. Flight time was calculated from the take-off and the subsequent landing. Jump height was derived by the following equation:

$$H = \frac{Gravity \times t_f}{8} \quad (1)$$

Reactive strength index was calculated as shown in equation 2.

$$RI = \frac{H \text{ (mm)}}{t_s \text{ (ms)}} \quad (2)$$

Landing and take off were estimated from the acceleration in vertical direction. Accelerometer data

were first filtered by a fifth order moving average filter. Landing was then defined as the beginning of at least five consecutive data values including a gradient larger then 400. With a delay of 90ms, beginning at landing, a local minimum in the range of 240ms is defined as takeoff. Figure 5 indicates exemplarily acceleration data including first landing (1), take off (2) and second landing after the jump (3). All data processing was performed on-board.

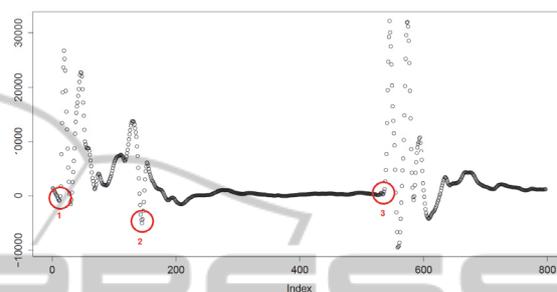


Figure 5: Filtered accelerometer data from a drop jump off of a box raised 31.5cm. The red points show the beginning of ground contact (1), the local minimum detected at take off (2) and the beginning of ground contact when landing after the jump (3).

Because of delays in onboard data processing when detecting a jump event,  $t_f$  was calculated by adding a correction factor of 20ms to the original value.

The IMU device was mounted close to the ankle as shown in Figure 6 with its x-Axis pointing vertically upwards.



Figure 6: IMU Device mounted close to the ankle.

To evaluate accuracy of event detection the provided information were compared with force platform data (AMTI BP 600400) sampled at 1000Hz. The validation study included ten participants (7 track and field athletes, 3 basketball players). Mean age was 25.1 years with standard deviation (SD) 3.45 years. Participants had a mean height of 186.3 cm, SD= 10.4 cm and a mean weight of 77.3 kg, SD= 12.45 kg. 3 were female and 7 were male. Overall, each participant performed 15 drop

jumps. A testing session consisted of 5 drop jumps from three different heights (31.5cm, 40cm and 50cm). Subjects stepped off of the box and performed their drop jump with each foot landing on the force platform. After each jump participants had a rest time of two minutes.

Statistical analysis was performed using R (Project for Statistical Computing). Bland-Altman plots for multiple observations per individual (Bland and Altman 2007) of  $t_s$ ,  $t_f$ , and RI were computed to assess the agreement between the developed device and force platform data. H was not included for the statistical analysis as no additional information was expected due to the its computation (see equation 1)

### 3 RESULTS

Overall, 141 out of 150 jumps were detected correctly which corresponds with a detection rate of 94 %. For  $t_s$  and  $t_f$  minimal differences of 0ms could be detected. After calculating H and RI, observations without differences between IMU and force platform occurred as well. A descriptive overview of the results of the evaluation study is given in table 1.

The 95% Level of Agreement (LOA) ranges from 9.82 to -8.13 ms for  $t_s$ ; 15.02 to -11.40 ms for

Table 1: Descriptive overview for parameters  $t_s$ ,  $t_f$ , H and RI. “mean diff” represents the mean difference between the device and force platform, “sd” its standard deviation, “min” represents the minimal occurred and “max” the maximal occurred difference during all correct detected jumps.

|       | N   | mean diff | sd          | min  | max    |
|-------|-----|-----------|-------------|------|--------|
| $t_s$ | 141 | 3.40 ms   | +/- 2.97 ms | 0 ms | 14 ms  |
| $t_f$ | 141 | 4.87 ms   | +/- 3.85 ms | 0 ms | 22 ms  |
| H     | 138 | 0.59 cm   | +/- 0.47 cm | 0 cm | 2.4 cm |
| RI    | 138 | 0.06      | +/- 0,05    | 0,00 | 0,22   |

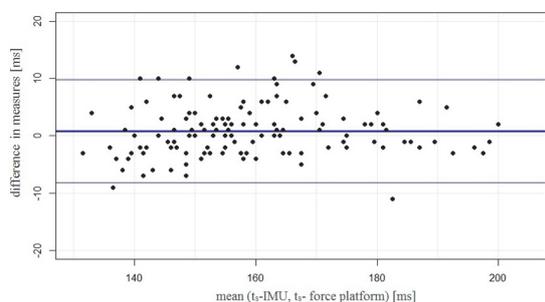


Figure 7: Bland- Altman plot comparing  $t_s$  determined by IMU and force platform data. The slight lines show the 95% confidence interval.

$t_f$  and 0.16 to -0.16 for RI. Figure 7 shows the difference in measures plotted against the mean of both measures on each trial for  $t_s$ .

### 4 DISCUSSION

The results indicate the developed device as a suitable tool for detecting selected parameters in a field based diagnostic. A group and ubiquitous monitoring is supported by the developed system. Multiple athletes can be assessed for diagnostics in the Android App by wearing the IMU.

However, the Bland-Altman results, specifically the confidence interval calculations, highlight some potentially important discrepancies between the force platform and accelerometer values. It is notable that our results and algorithm are only based on the accelerometer data, but nevertheless are comparable to results reported by Bergamini et al. (2012) and Patterson and Caulfield (2010). It is noteworthy, that the results include one participant with “bad” detections, which seems to be caused by technical difficulties in performing the Drop Jumps. Without this single participant mean differences for  $t_s$  between IMU and force platform decrease to 2.87ms and the 95% LOA to 7.48 to -7.31ms. The recent algorithm yields the advantage of less processing power to facilitate on-board processing and fast data broadcasting via Bluetooth low-energy. Further research will focus on the optimization of the algorithms. Promising approaches might be the use of gyroscope data supplemental as well as Kalman Filtering for data processing.

The developed IMU device promises an optimization of plyometric training or even technique training in jumping events by objective feedback of crucial performance parameters. Monitoring fatigue in repeated jumping or 400m sprinting, as example, might also be an interesting area of application.

Therefore, further research aims to develop an algorithm to detect parameters like stance and flight durations or step lengths and frequencies in sprinting with a satisfying accuracy.

The continuous monitoring of multiple movements will also allow analyzing movement variability as a feature of expertise. Former studies in badminton showed that expertised athletes not tend to show higher manifestatitons of performance parameters but stable results in repeated executions (Jaitner and Gawin, 2010). Regarding stability and variabilty of chronometrical influencing variables only less empirical evidence is given for elite sports

in track and field. To investigate this is a main aim of further research for example in hurdling.

The use of the developed device in field based studies will probably result in a deeper understanding of how to design training programs to optimize explosive performance like jumping and sprinting in elite track and field athletes.

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