Open source bio-logger for monitoring and recording inertial movement

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***Abstract*—There is a growing interest for bio-logging and the measurement of animal or human motion. However, most of the technical solutions are commercial and therefore fit hardly to particular needs. Here, we describe in details an Arduino-based stand-alone logger featuring a 32-bit microcontroller, an IMU, a Bluetooth link and a SD card. Angular speeds and 3D orientations measurements (roll, pitch and yaw angle) of the hydrofoil are done at a sampling frequency of 100 Hz while the kiteboard is moving in the open sea. Software and hardware design are made fully available on an open archive to facilitate the development of such device.**

***Index Terms*—inertial measurement unit, data logger, sport, hydrofoil**

I. Introduction

A bio-logger is a device attached to an animal or a human in order to record data about their movement (position, speed, temperature, etc...) and their surroundings. Bio-loggers have been originally developed for studying birds and marine animals (see [4]), and have been extensively used for fully automated monitoring of a wide variety of terrestrial and marine organisms [9, 10, 11], see Williams et al. for a review [14]). Nowadays, many bio-loggers are available on the market (Wildlife Computers, Little Leonardo, Star Oddi...), however, they rely on proprietary hardware and software architecture which leaves little room for customization. In addition, most studies on animals or humans use only a portion of what could be done with these sensors [6].

Recently, it has been shown that Euler angles could be derived from attitude estimation algorithms such as the one proposed by Madgwick [5] on the basis of accelerometer, rate gyro and magnetometer signals composing the so-called Inertial Measurement Unit (IMU). Inertial studies have found an interest in sport performance evaluation [7]. In their recent systematic review, Camomilla et al. have evaluated the usefulness of magneto-inertial sensors for sport performance metrics during training or competition [3].

The present work details an open-source magneto-inertial sensor encased in a data logger originally designed for measuring pitch, roll and heading to reconstruct head-body movements in penguins and which is applied here to a hydrofoil kiteboard. Kiteboarding is a worldwide sport featuring 1,5 millions kitesurfers. Inertial sensor have already been used for the study of the motion of the kite itself [8], or to measure jump height [2]. Here and for the first time, we show that inertial data logging of the kiteboard can provide useful information on other parameters, such as turning rate amplitude, pitch and roll angle values during straight trajectories and synchronized movement analysis during heading changes (maneuvers).

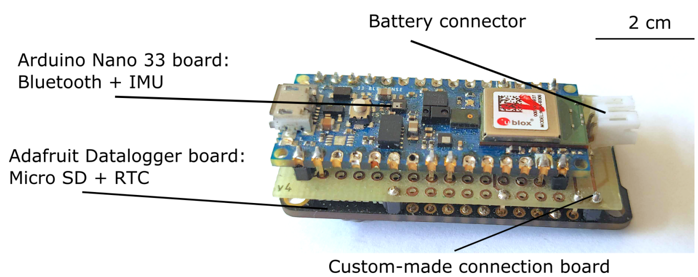

Fig. 1. Data logger design for onboard recording as a stand-alone device. Yaw, pitch and roll angles are recorded at 100 Hz.

II. Stand-alone data logger

A. Hardware description

Figure 1 shows our magneto-inertial data logger, constructed with off-the-shelf components: the core controller is an Arduino-compatible Nano 33 board wired via a custom-made connection board to an Adafruit data logger board. The latter includes a micro SD card for recording the data and a real-time clock circuit (RTC) for dating the recorded files. The Arduino board includes a 9-axis IMU and a Bluetooth LE chip for wireless communication with external devices. Finally, a single cell lithium-polymer battery was used for powering. The component specifications and costs are summarized in table I.

TABLE I
COMPONENTS SPECIFICATIONS AND COSTS

Component	Size	Mass	Cost
Nano 33	**18x44** mm^2	5.8 g	27 €
Adafruit Logger	**21x51** mm^2	6 g	9 €
LiPo Battery	**17x31.4** mm^2	6.2 g	9 €
3D printed package	**65x27x27** mm^3	19 g	1 €

B. Software description

The logger software was written in C with the Arduino IDE. A fully annotated version that describes the program flow and functionality can be downloaded on Github [13]. The program is based on standard Arduino libraries to address the various peripherals of the microcontroller. Time is a very critical parameter when dealing with bio-logging. To ensure a constant sampling time, timing interval, in milliseconds, between two successive acquisitions was measured. The time-lapse is then compared to a threshold set to 10ms, and supplementary acquisition points can be done if the time lapse is superior to the the threshold. Later, in section III-B, the performance of this strategy is provided.

Sensor raw values (accelerations, angular rates, magnetic inclinations) are recorded on the SD memory card every 10 ms. More, from these raw values, the three Euler angles are computed simultaneously and at the same time, leading to a total of 13 parameters recorded every 10 ms. The logger can be remotely controlled with the Bluetooth Low Energy interface (BLE), by sending control commands to start, stop the acquisition or read the sensor values. Hence, the three Euler angles can be sent via BLE on request, Which is particularly useful once the logger is secured in its sealed waterproof package without any external button. The two programs written in python that are used to fully control the logger are provided for a linux or an IOS interface.

III. FIELD TESTS: KITEBOARD ATTITUDE MEASUREMENT

Prior to field tests, the logger was calibrated following the procedure described in the Arduino LSM9DS1 library, written by Verbeek [12]. As water is not compatible with electronic components, the electronic boards and the battery were secured in a waterproof plastic bag (a condom) and then placed in a custom 3D printed box. This waterproof logger is then fixed to an aluminum fuselage of a hydrofoil (IC6V2, FOne, France) with an adhesive rubber band (Electrical tape, 3M, USA). The place of the logger on the fuselage was chosen to reduce hydrodynamic perturbation and let the hydrofoil work normally. The fuselage is tightly screwed to its corresponding aluminum mast which is fixed to a kiteboard (custom made). The Figure 2 shows the hydrofoil used for this study and the logger in its waterproof casing on the fuselage.

The man chosen for the experiment, which is one of the author, has 3 years of learning hydrofoil and could be considered as a skilled kitesurfer. He was asked to record its trajectories from a GPS watch (Ambit3 Peak, Suunto, Finland). This measure is computed to find an estimation of the heading, which is then compared to the heading metric provided by the logger. At the very beginning of the experiment the logger was immersed into water at a depth of 90 cm, i.e., the length of the mast between the hydrofoil plane and the kiteboard. Then, during the experiment the logger was at a depth of around 40 cm, which is the usual functional depth of a hydrofoil designed for kitesurfing. The Figure 3 shows the 23 minutes GPS record from the GPS watch. During the experiment 13 straight two-way trajectories were recorded of about 400 m long each. The average speed was about 8 m/s (*i.e.*, 29 km/h), a value which is coherent with the 32 km/h wind speed measured on the day we conducted the experiment in Marseille, France (source [1]).

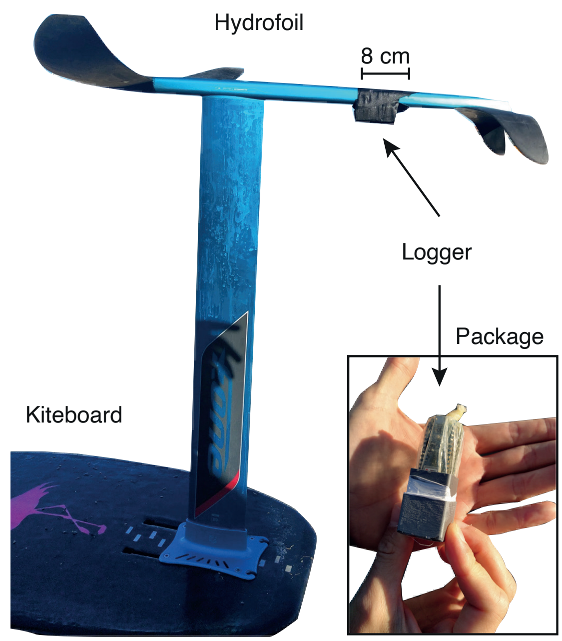

Fig. 2. Hydrofoil of the kiteboard equipped with the logger. The logger is encapsulated in a condom to make it waterproof before being placed in a custom 3D printed box.

A. Data processing

Figure 4 shows the three Euler angles, their corresponding rate being related to angular speed. The latter was obtained by filtering the raw signals with a one-dimensional median filter (dimension to filter along of 200 samples), then the filtered signal was differentiated and then filtered again with a median filter (dimension to filter along of 100 samples). From the Figure 4 we see that a large change in the heading by about $180°$ is accompanied by a change of roll of about $50°$ ($\pm 25°$).

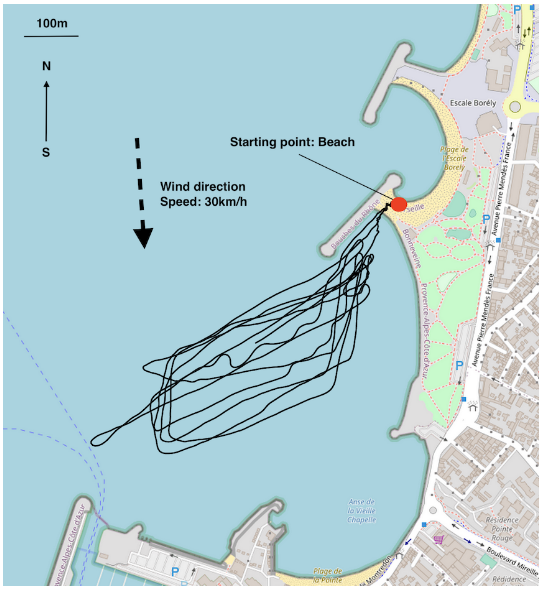

Fig. 3. Trajectories of the kitesurfer recorded with a GPS watch at 1 Hz. The starting and end points are the point indicated by the red dot.

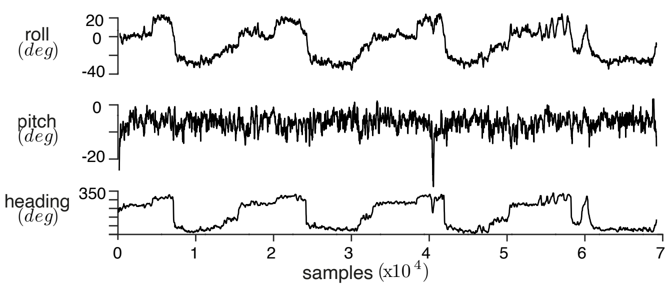

Fig. 4. Measured Euler angles (roll, pitch, heading) samples.

Also, the pitch was very constant during the whole experiment and was equal to $-7.2° \pm 11.6°$, which corresponds to a slight pitch up of the kiteboard. In addition, the angular speed was relatively low in pitch and roll (inferior to $10°/s$) but the heading rate was high during the maneuvers. This metric could be interpreted as an evaluation of the ability of the kitesurfer to change more or less rapidly the heading.

Figure 5 shows the heading measured by the logger (black) along with the estimated heading from the GPS watch (grey). The heading estimated from the GPS at a sample number i was calculated as:

$$H_{eading}^{GPS}(i) = \arctan 2\left(\frac{Y_{pos}(i) - Y_{pos}(i-1)}{X_{pos}(i) - X_{pos}(i-1)}\right) \quad (1)$$

where,

$$X_{pos} = R * \lambda \text{ and } Y_{pos} = R * \phi \quad (2)$$

where R is the radius of the earth equal to 6371 km, λ is the longitude and ϕ the lattitude in radian.

The speed of the kiteboarder (Fig. 5) was calculated as:

$$S_{peed}^{GPS} = \sqrt{diff(X_{pos})^2 + diff(Y_{pos})^2} \quad (3)$$

with *diff* the approximate derivative function (difference between adjacent elements).

As the two headings cannot be synchronized during the experiment, we applied a post hoc time correction from the calculation of the cross correlation function between the heading signal measured by the logger and the GPS estimated heading calculated from 1. The time lag between the two signals corresponds to the maximum correlation found here to be equal to 67 samples. The heading measured from the logger was filtered by means of 1D median filter (dimension to filter along of 140 samples). The Figure 5 indicates an excellent correlation between the two heading signals, validating the good accuracy of the logger.

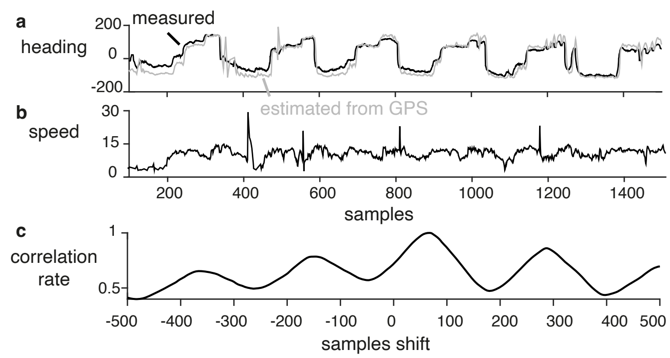

Fig. 5. **a**. Measured heading from the logger (black) and estimated heading from GPS (grey). **b**. Linear speed of the kiteboarder calculated from the GPS positions. **c**. Correlation rate used to synchronize the heading signals.

B. Real-time acquisition performance

The performance of the real time acquisition is assessed from the fine measure of the time-lapse between two successive acquisitions. Histograms of this time-lapse has been plotted as a proxy of the performance. To compare different computational burden of the micro-controller, we studied 3 cases:

- case 1: only tri-axes accelerometer signals are recorded on the SD card, Euler angle computing is disabled
- case 2: tri-axes accelerometer signals and computed Euler angle are recorded on the SD card
- case 3: all signals of the magneto-inertial sensor and the three Euler angles are recorded on the SD card

Histograms shown in Figure 7 were computed with 200 bins for each case. As expected, over a total of 105000 samples, we obtained a large number of time intervals equal to 10 ms, which correspond to the sampling time: from 86000 in case 3 up to 99000 in case 1. However, the number of lapses of time equal to 20 ms was a bit higher in case 3 due to a higher quantity of data to record on the SD card. In any case, this test confirmed the good performance of the data logger in terms of real time acquisition.

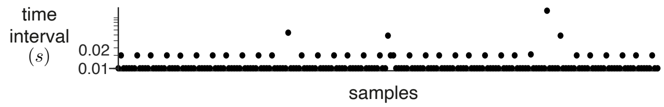

Fig. 6. An example of sampling time measurement.

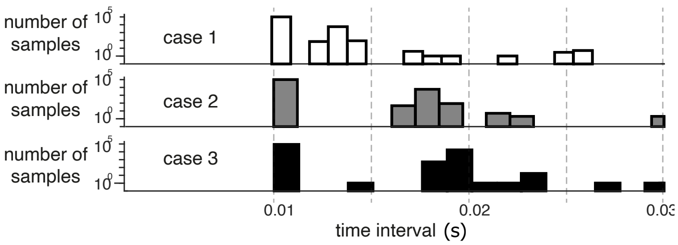

Fig. 7. Histograms of the time computation for: -case 1- where only the accelerometer is recorded on the SD card, -case 2- where the Euler angles are added to the record and -case 3- where all the signals of the magneto-inertial sensor are recorded including the Euler angles

IV. Conclusion

We described here the design and performance of magneto-inertial sensor able to measure and record in real time the 3D orientations based on Euler angle of an hydrofoild fixed to a kiteboard. Angular velocities along the sensing axes were also estimated. We compared the measured heading with the estimated heading from a GPS watch and showed an excellent correlation despite the fact that the heading measurement was done into the sea at a depth of 40 cm. We are now working on a highly miniaturized version ($26 \times 31 \text{ mm}^2$) of the logger in order to reduce its impact on the hydrodynamics of the hydrofoil or other bodies it would be attached to. In addition, it could be valuable to compare the orientation provided by the logger with another logger placed for example on the leg of the kitesurfer.

Acknowledgment

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