Accurate Boomerang Rotation Speed Estimation from Low-Cost IMU

TAKUMI KONDO[1] YVAN MADEC[2] PIERRE MARET[3] GUILLAUME LOPEZ[1]

Abstract: In recent years, some research and techniques have shown many approaches for analyzing the athlete movement with sensor data. A smartphone's application is already available to provide feedback without an instructor by analyzing the user movement with device mounted sensors. To ease boomerang learning, we are developing a smart boomerang mounted a low-cost IMU sensor and a high-cost gyroscope. In the future, to be able to sell smart boomerangs as off the shelf, it will be necessary to remove the high-cost gyroscope. However, the gyroscope value of the IMU sensor saturates while the boomerang is flying. On the other hand, the high-cost one has enough performance. In this study, we estimated the high-cost gyroscope value in the range of low-cost gyroscope saturation using other sensor values. As a result, the polynomial estimated formula of the second degree using x-axis acceleration has enough good accuracy to make up for the high-cost gyroscope.

1. Introduction

Boomerang as a sport first began in the USA around 1965. Thanks to the increase of boomerang lovers worldwide, World Boomerang Championships have been held every two years since then. While boomerang lovers are increasing, it's more difficult for boomerang beginners to receive instruction directly from a specialist than some sports. To ease boomerang learning, we are developing a smart boomerang, that would enable displaying trajectory and advise on user's smartphone using boomerang mounted sensors.

2. Related Work

Along with the widespread use of wearable sensor devices, research and techniques for analyzing the movement of bodies, and gears from acquired data are progressing in sports fields. In the field of skills science, some research proposes to attach sensor devices to a tennis racket[1], or to the wrist of the player[2], to enable the analysis of players motion.

Kos et al. have proposed the SmartSki system, including measuring equipment integrated sensors and applications for improving the skiing skill level and performance[3]. Also, Technical Pitch enables the analysis and feedback of baseball pitching metrics such as ball velocity, spin axis, and spin rate on smartphone throwing a ball which contains a 9-axis inertial motion unit (IMU)[4]. This device is already available on the market, and users can easily receive feedback concerning pitching from it.

As an application of these researches, Lopez et al. developed a sports skill improvement support system using smartwatch sensors and feedback screen[5]. They have shown that on-site feedback based on analyzing the movement from acquired data is effective for individual skill improvement.

3. Boomerang Prototype

We prepared a boomerang prototype for realizing smart boomerang (Figure 1, Figure 2). Boomerang prototype embeds a High Dynamic Range (HDR) gyroscope (z-axis only, Max 20000 degree/s, 500Hz), a Low Dynamic Range (LDR) gyroscope (3-axis, ± 2000 degree/s), an accelerometer (3-axis, ± 16 g, 500 Hz), and a magnetometer (3-axis, $\pm 4800\mu T$, 100 Hz).

Since the most significant motion of a boomerang is the rotation, a gyroscope is very important. As described above, the boomerang prototype has LDR and HDR gyroscopes. As shown in Figure 3, the LDR gyroscope becomes saturation while boomerang is flying. On the other hand, the HDR gyroscope can get sensor value without becoming saturation. So, it showed that the HDR gyroscope has enough performance to analyze the boomerang's movement.

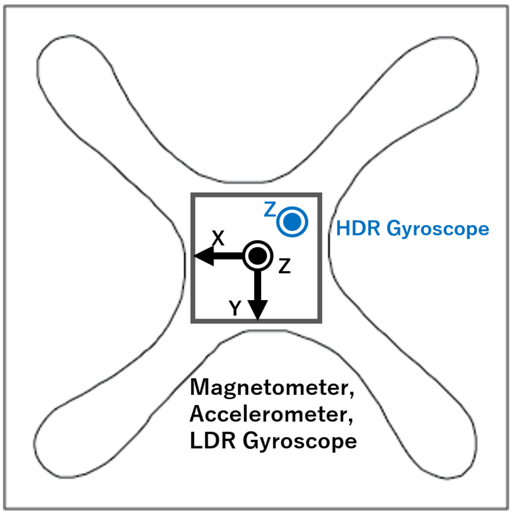

Fig. 1 Schematic of the Smart Boomerang Prototype

1 Aoyama Gakuin University
2 DARWIN BOOMERANGS
3 University Jean Monnet

Fig. 2 The Smart Boomerang Prototype

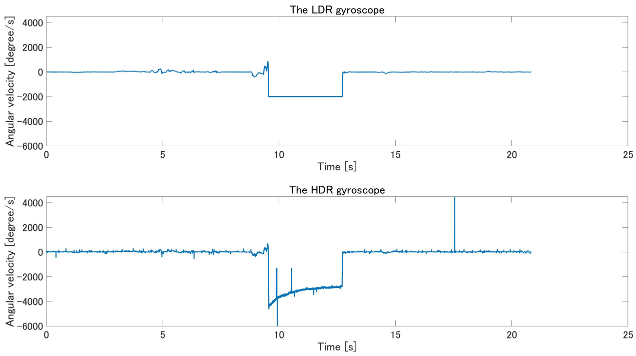

Fig. 3 Z-axis gyroscope sensor values

Fig. 4 A boomerang athlete threw the boomerang prototype for data collection

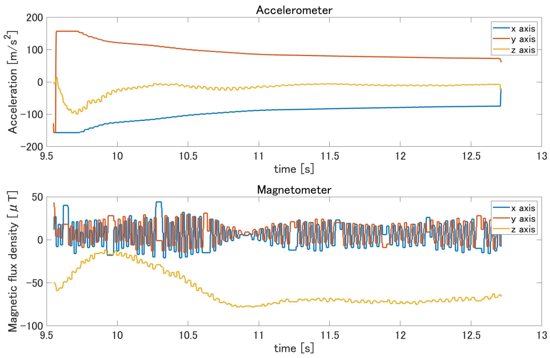

Fig. 5 Sensor data in the range of the LDR gyroscope saturation

However, it is an expensive sensor compared with the others. In the future, to be able to sell smart boomerangs as off the shelf, it will be necessary to remove the HDR gyroscope. This study aimed to evaluate how accurate we can estimate HDR gyroscope values from other low-cost sensors data.

4. HDR Gyroscope Values Estimation

4.1 Data Collection and Preprocessing

We collected sensor data from throwing to catching boomerang. In this study, a boomerang athlete who won World Boomerang Championships threw and caught the boomerang prototype for data collection (see Figure 4). Acquired sensor data are sampled at 1000Hz. And 3-axis accelerator unit are converted from g to m/s^2. While sensor data does not saturate, the LDR gyroscope values are identical to the HDR ones. We need to estimate HDR gyroscope sensor values using other sensors in the range of the LDR gyroscope saturation.

First, we removed noises from sensor data. As shown in Figure 3, there are noises such as sudden big noises within signals. To remove noises, we applied each sensor data to the median filter (window size is 25 samples).

Next, we extracted sensor data in the range of the LDR gyroscope saturation to use the estimation of the HDR gyroscope value. Figure 5 shows that both x-axis and y-axis acceleration become saturation for a very brief moment. So, we extracted and used the range of the LDR gyroscope saturation, excluding this period for the estimation.

4.2 The estimation result of the HDR gyroscope Using Curve Fitting

Then, we computed the polynomial equation of the second degree using the HDR gyroscope value and the other two sensors values while the LDR gyroscope and both x-axis and y-axis acceleration saturate by executing curve-fitting on MATLAB. To find the best combination of two sensor values, we tried to compute the polynomial equation of 15 combinations and compared the results. As a result, Table 1 shows the combination of the x-axis acceleration and y-axis acceleration had the best adjusted R-square value. Besides, it should not be necessary to use both x-axis and y-axis acceleration due to the 90° phase shifting. We evaluated the estimation accuracy of the HDR gyroscope value while the LDR gyroscope and both x-axis and y-axis acceleration saturate, using only x-axis or y-axis acceleration.

To estimate the HDR gyroscope values from x-axis or y-axis acceleration values in the saturation period, we used polynomials estimation of the first-degree, second-degree, and third-degree. As shown in Table 3, every results got good score. Further, we evaluated these polynomial formulas using the HDR gyroscope values in the range of the LDR gyroscope ones. As shown in Table 3, these results

Table 1 Adjusted R-square by 15 different sensor combination

Input 1	Input 2	Adjusted R-square
X axis accelerometer	X axis magnetometer	0.994
	Y axis magnetometer	0.994
	Z axis magnetometer	0.994
	Y axis accelerometer	0.995
	Z axis accelerometer	0.994
Y axis accelerometer	X axis magnetometer	0.991
	Y axis magnetometer	0.991
	Z axis magnetometer	0.992
	Z axis accelerometer	0.992
Z axis accelerometer	X axis magnetometer	0.677
	Y axis magnetometer	0.623
	Z axis magnetometer	0.915
X axis magnetometer	Y axis magnetometer	0.0717
	Z axis magnetometer	0.814
Y axis magnetometer	Z axis magnetometer	0.812

also got good scores. From these evaluations, the best polynomial estimation formula is the polynomial equation of the second degree using an x-axis accelerator according to formula (1). In formula (1), $f(x)$ is the estimation value of z-axis gyroscope in degree/s, x is the x-axis accelerator in m/s^2. Mean Absolute Percentage Error (MAPE) is 0.88%.

Figure 6 shows the best quadratic fitting result, and figure 7 shows the HDR gyroscope signal and quadratic estimation using x-axis acceleration values when the LDR gyroscope saturates.

$$f(x) = 0.02514x^2 + 21.43x - 1345 \quad (1)$$

5. Conclusion and Future Works

In this study, we estimated the HDR gyroscope sensor value when the LDR gyroscope sensor value achieves saturation using low-cost IMU sensor values. The polynomial estimation formulas using x-axis acceleration or y-axis acceleration have good results. Among them, the polynomial formula of the second degree using x-axis acceleration is the best (0.88% MAPE).

However, since this study used only one dataset, we need to prepare and validate more datasets. Since both x-axis and y-axis acceleration value achieve saturation for a very brief moment while the boomerang is flying, it is necessary to replace the low-cost IMU sensor by a high performance one or to validate whether other sensors can accurately estimate both x-axis and y-axis acceleration value.

As a prospect, we plan to extract essential data about boomerang flight (boomerang rotation speed and angle of inclination, etc.) using these sensor values for developing smart boomerang. Using these essential data, we would

Table 2 MAE and MAPE values in the range of both x-axis and y-axis acceleration and HDR gyroscope saturation

Input	Order	MAE	MAPE [%]
X axis accelerometer	1	21.5	0.686
	2	19.3	0.621
	3	19.2	0.616
Y axis accelerometer	1	22.6	0.724
	2	18.9	0.616
	3	19.0	0.616

Table 3 MAE and MAPE values in the range of HDR gyroscope saturation

Input	Order	MAE	MAPE [%]
X axis accelerometer	1	28.8	0.900
	2	28.3	0.876
	3	29.6	0.902
Y axis accelerometer	1	48.8	1.45
	2	62.9	1.86
	3	84.6	2.51

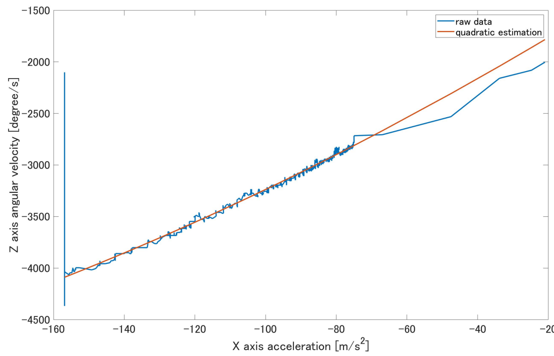

Fig. 6 Sensor data in the range of the LDR gyroscope saturation

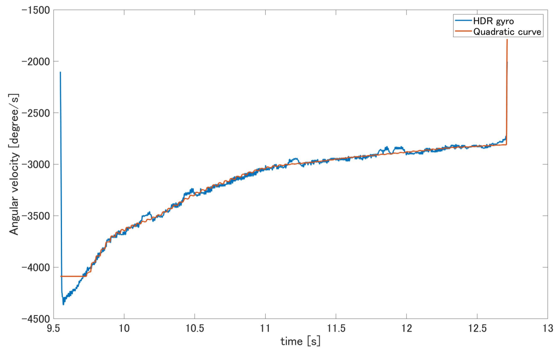

Fig. 7 Sensor data in the range of the LDR gyroscope saturation

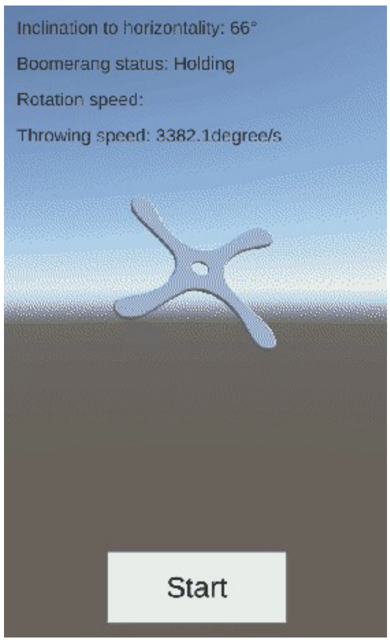

Fig. 8 Smartphone application received key data about boomerang fright from the smart boomerang

provide feedback to encourage boomerang skill improvement on smartphone's application for boomerang beginners (Figure 8). In the future, we want to launch smart boomerang and feedback application.

References

[1] D. Masuda, K. Tasaka, T. Ohgishi, and S. Obana. Proposal of progress assist system for tennis using wearable sensors. In *Multimedia, Distributed, Cooperative and Mobile Symposium (DICOMO'2014)*, pages 545–52. IPSJ, 2014.

[2] K. Saitou, Y. Ohgi, S. Inoue, H. Ichikawa, M. Yamagishi, C. Miyaji, and S. Takai. Estimation of ball speed in baseball pitching from acceleration measured at the wrist. 47:41–51, 2002.

[3] Anton Kos and Anton Umek. Smart sport equipment: Smartski prototype for biofeedback applications in skiing. *Personal Ubiquitous Comput.*, 22(3):535–544, June 2018.

[4] Technical pitch. `https://technicalpitch.net/`.

[5] G. Lopez, S. Abe, K. Hashimoto, and A. Yokokubo. On-site personal sport skill improvement support using only a smartwatch. In *2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, pages 158–164, 2019.