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A Low-cost Mobile Real-time Monitoring System for Analyzing Head Position and Breathing Patterns in Front Crawl Swimming

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Abstract. Swimming posture analysis usually requires video-based equipment with high installation costs and time-consuming data processing. Wireless transmission and real-time monitoring data, by contrast, are much desired by swimming coaches, learners, and athletes. The objective of this study aims to modify an inertial measurement unit (IMU) using the Bluetooth Low Energy (BLE) wireless communication protocol and place it on the back of the swimmer's head to measure the pitch and roll of the head during front crawl swimming. The data obtained from an IMU can be monitored on an Android mobile device in real time, stored in the mobile device's built-in memory, and later uploaded to Google Drive for post analysis. An algorithm was also developed for counting the number of breaths taken to the left and to the right for breathing pattern analysis. To verify the feasibility of the proposed system, a case study was performed in which two swimmers of different abilities wore the proposed device while front crawl swimming. Analysis of the data obtained from the two swimmers indicates that the proposed system can successfully identify the pitch and roll angles of the head, while the proposed algorithm counts the number of breaths taken to the left and to the right. Further analysis of the descriptive statistics of the pitch and roll angles reveals the differences between the head position of the two swimmers when they took a breath during front crawl swimming, thereby providing the coaches and swimmers with objective reference data to help them improve their swimming technique and verifying the feasibility of the system developed in this study.

Keywords: Bluetooth Low Energy, inertial measurement unit, front crawl swimming, breathing pattern

1 Introduction

Swimming is a sport that relies heavily on motor skills. Without proper limb movement and torso balance in the water, a swimmer will sink or be unable to propel forward efficiently. Recreational swimmers, in particular, have not received as much training as professional swimmers, and they do not have the environment or equipment to obtain data related to their own swimming posture to tell them what they need to correct. To observe swimmers' motion, video-based equipment and inertial measurement units (IMU) were widely applied in past research, and these two technologies will also be reviewed in this section.

1.1 Video-based Equipment Used in Swimming Research

In practice, video segments must be digitized on a computer by a coach or sports scientist for processing and analysis [1-2]. Post analysis and processing is time-consuming and does not immediately provide swimmers with feedback on how to improve their motor skills. Capturing underwater motions requires at least one piece of underwater video-based equipment, and tracking the motions of the swimmer during

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each lap requires an underwater rail camera. Although underwater cameras can capture motions underwater, such installation is expensive and complicated. These limitations make it difficult for such devices to be installed in venues not intended for professional training [3]. Furthermore, how swimmers perform in experimental scenarios is likely to be different from how they perform in natural circumstances [4].

On the whole, using video-based equipment to analyze swimming motions have the following shortcomings [5-8]:

1. long installation time;
2. complex installation in experimental environments;
3. high equipment costs;
4. time-consuming post-processing and motion analysis of videos, thereby preventing instantaneous feedback;
5. disturbance from water flow, light reflecting off water surfaces, and foam affecting video capture and interpretation;
6. parallax preventing capture of motion details.

1.2 Inertial Measurement Units Used in Swimming Research

To solve the above mentioned disadvantages of video-based technology, researchers may utilize electronic sensors to acquire swimming data. In recent years, advances in electronic technology and sensor miniaturization have enabled sensors to be directly worn by athletes. These sensors record the motions and responses of the swimmers, offering a possible alternative to swimming analysis systems with video-based devices. An inertial measurement unit (IMU) is the general term for such sensors, including accelerometers, gyroscopes, and magnetometers. A single IMU may contain one to all three of these sensing elements. Over the past 20 years, IMUs have proven to be powerful tools for swimmer posture analysis [8]. In addition, the application of IMUs is not limited to certain experiment venues or laboratories. IMUs can be used to obtain measurements in natural swimming environments and can gather more swimming data than can be obtained in limited experimental environments [9].

According to a review conducted by Mooney et al. [8], studies that used IMUs to examine swimming motor skills can be divided into the following aspects:

1. stroke phase analysis;
2. stroke type identification;
3. lap time;
4. swimming distance;
5. number of strokes and stroke rate;
6. swimming speed;
7. number of kicks and kick rate;
8. joint or body angle analysis;
9. biomechanical parameters;
10. start and turn motions.

1.3 Batch and Real Time Data Acquisition from IMUs

The vast majority of IMUs store the data they collect in SD memory cards or built-in storage memories during experiments. After the IMUs are extracted from the swimmers, the data are transferred to a computer via USB or a wireless connection for post analysis. However, built-in memories or SD memory cards for data storage increase power consumption and MCU computation loading, and coaches and sports scientists cannot see the swimmer data in real time. As a result, only a few studies use IMUs with wireless real-time feedback to analyze swimmer motions [10-12, 15].

However, the real-time feedback function is crucial for users. Mullane et al. [13] conducted an investigation to understand what basic frameworks a graphical user interface (GUI) would need for swimming data analysis. Their investigation revealed that the real-time monitoring functions took up 9 of the 17 aspects in system requirements, and among these 9 aspects, 5 were ranked the most needed by coaches, sports scientists, athletes, and recreational swimmers. This shows that functions associated with real-time monitoring are the primary considerations in the development or selection of swimming data analysis systems. The empirical study conducted by Jefferies et al. [14], which used multiple cameras in a tank experiment environment to provide real-time images, also indicated that if swimming performance data could be displayed to and analyzed for athletes and coaches in real time, the generating force and swimming speed of athletes could be increased by 20% in a two-hour training session. This shows how helpful real-time information and feedback is to coaches and athletes.

Efforts have been made on using real-time sensing system to provide instantaneous feedback for athletes and coaches. The system developed by Hagem [10] uses optical transmission to display stroke rate and stroke distance on the swimmer's goggles, but cannot transmit data to poolside coaches or sports scientists.

Sage et al. [11] created a wireless real-time feedback system installed on a swimmer's waist. The circuit board is divided into two parts: a micro control unit (MCU) board and an IMU board, the dimensions of which are 30mm×40mm and 90mm×30mm, respectively. An antenna is attached to the MCU; however, their paper did not explain the installation of antenna or power supply that was used to achieve the claimed transmission distance of 35-m. To provide real-time feedback, an RF radio is employed to transmit data at a sample rate of 25 Hz on the industrial scientific medical (ISM) band. They developed their own non-standard protocol for transmission, which comprised a physical layer, a network layer, a transport layer, and a customer application layer. Due to the custom software and hardware protocols, the non-universal system, and the fair size of the entire device, its actual promotion would be limited.

The wireless transmission distance of the system developed by James et al. [12] is short: less than 2-m. It may only be suitable for flume experiments rather than for real-world races and practice sessions. They also developed their own transmission protocol rather than use a universal wireless transmission protocol. Their software system was created using MATLAB, which is only suitable for academic research environments; general users would struggle to make real-time observations using this kind of system.

Lecoutere and Puers [15] developed a wireless IMU device based on the Texas Instruments (TI) product CC430. The built-in MPU6000 in the device comprises an accelerometer and a gyroscope and is equipped with 64 Mb of memory, which can record 116 minutes of IMU raw data. At a sample rate of 40 Hz, the device can transfer 16-bit data packets using RF wireless transmission. The dimensions of the device are 16mm×12mm×10mm. However, in their paper they did not provide the type and size of the battery or the overall weight and waterproof treatment of the device. The size of a device is generally several times that of an IMU following waterproof treatment or the addition of a waterproof casing [16]. Although their study provided schematics of the proposed framework and the device on the back of the head, they did not show any photos of the actual product or describe how to install it. Furthermore, they did not explain how they dealt with the wireless transmission antenna or what transmission protocol they used. Specifications provided on the TI website [17] indicate that transmission to a computer requires a USB transceiver that TI specifically developed for this IMU, but no information was given regarding the computer equipment receiving the data or the data analysis software. Clearly, the device uses its own special protocol for wireless transmission rather than universal protocols such as Wi-Fi or Bluetooth, which will greatly limit the development and promotion of its software and hardware.

1.4 IMU Installation

So far, studies that have used IMUs to analyze swimming motions have mostly installed the IMUs on the upper limbs [8] to analyze hand motions. However, few studies have analyzed head motions and breathing patterns in front crawl swimming. Front crawl is the fastest and most efficient swimming stroke of the four primary strokes (front crawl, backstroke, breaststroke, and butterfly). Swimming coaches use front crawl to train swimmers for improving their aerobic capacity and distance [18]. Thus, front crawl is a fundamental swimming technique that serious swimmers must master. Additionally, leg kicks, hand strokes and body orientation are the noticeable actions of front crawl swimming. Proper body orientation stabilizes the trunk and keeps the body in a streamlined position to reduce hydrodynamic drag. To keep body in a streamlined during swimming, the head must be aligned with the torso as much as possible to reduce drag. Thus, whether a straight body line can be maintained is a primary focus in the observation and assessment of posture in front crawl swimming [19]. The roll angle of the body while taking a breath is greater than normal, which causes the body to lose its streamlined shape and increase drag. Thus, the pitch and roll angles of the head should be as small as possible. Cortesi and Gatta [20] dis-covered that when the head is down and below extended arms, its passive drag is 10.4~10.9% lower than that when the head is up. These factors make the head a good location for an IMU. Furthermore, installing an accelerometer on the head does not interfere with swimmer motions as much installation on the swimmer's limbs does [8].

Pansiot et al. [6] also analyzed locations for IMUs and observed that devices worn on the torso or head are suitable for the four primary swimming strokes. These locations are also suitable for obtaining data regarding overall motions. Pansiot et al. modified an ear-worn activity recognition sensor and fastened it to the left rubber strap of the swimmer's swimming goggles to analyze the pitch and roll angles of the head. However, it could not instantaneously transmit data to a mobile device or computer.

1.5 Research Motivation and Purpose

As shown in the above literature review, there are several salient points of previous studies worth noting here:

1. costs and complexity of IMU installation;
2. standard protocols to acquire swimming data;
3. general user-centered designed systems for swimmers and coaches;
4. instantaneous observation of body or head position during front crawl swimming;
5. data storage for post analysis;
6. analysis of head position during front crawl swimming.

To facilitate improvement of swimmers who use front crawl strokes, research concerning the key points above must be carried out in order to reduce costs, installation complexity, and data processing time for IMU-based data acquisition systems. Therefore, the specific aims in this study address the following:

1. undertaking an easy, affordable, and water resistant installation of IMU;
2. using standard wireless protocol such as Bluetooth 4.0 for wireless and real-time data transmission;
3. developing mobile applications that are easy to install and use;
4. associating with a mobile or portable device that can display instantaneous swimming data;
5. transmitting data to a mobile device or a cloud drive for post analysis;
6. proposing an algorithm to automatically detect head movements during front crawl swimming.

2 Method

This section explicitly details the hardware, firmware, and the Android application of the proposed BLE system. The method of data acquisition is also included.

2.1 Hardware

Most extant studies used self-developed transmission protocols and RF transmission. In practical applications, some hardware resources can only be obtained from certain manufacturers, and universal protocol libraries cannot be used for their software design. This study thus focused on hardware with Bluetooth communication capabilities from the beginning.

The hardware manufactured by Nordic Semiconductor is based on the NRF51822 Bluetooth chip which contains an MCU and offers well-developed and well-supported libraries, rendering it suitable for researchers developing their own hardware and software. The micro-module designed open-sourced library and hardware framework of the NRF51822-based platform and the NRF51 Sensor Tag (hereafter referred to as the sensor tag), as shown in Fig. 1, served as the hardware development platform in this study. Details on the circuit layout and relevant libraries can be found on the manufacturer's website [21]. The size of the platform is 3cm×3cm×1.2cm. It weighs approximately 90 g, costs around $20, and uses a CR2032 battery for the power supply. Aside from the built-in Bluetooth 4.0 BLE communication, it also contains an IMU MPU6050, which combines a 3-axis accelerometer and a 3-axis gyroscope, BMP 180 temperature and atmospheric pressure sensors, which can be used to measure temperature and height, and an AP3216C ambient light sensor. Regardless of the sensoring capabilities of the hardware platform, only the data provided by the IMU MPU6050 were retrieved in this study, as the current focus is on efficiently and accurately detecting head movements. Fig. 2 displays the block scheme of the sensor tag.

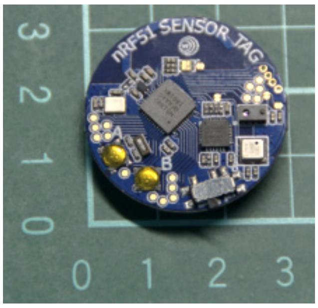

Fig. 1. NRF Sensor Tag

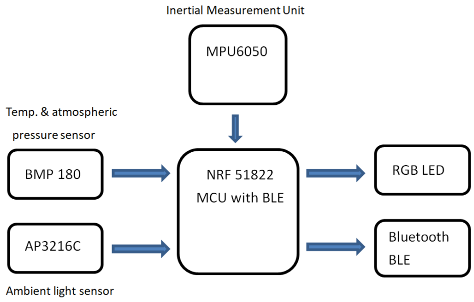

Fig. 2. Block scheme of hardware platform

2.2 Firmware

The hardware platform already has factory burn-in firmware, but was unusable for several reasons. First, the format of the output data from the factory firmware has not been clearly specified by manufacturers. Second, the manufacturer's Android application reads sensor tag data that includes raw data from the IMU, ALS, and the BMP180. However, only the IMU data with direct output of pitch and roll angles were relevant to this study, so the factory firmware did not meet the current needs. Finally, reading data from multiple sensors consumed more power, so the firmware of the sensor tag needed to be redeveloped.

Developers on the MySensors public forum [22] suggested using Mistry's libraries [23] developed for chips of NRF51 and NRF52 series to write firmware program for the sensor tag. The how-to description files of Mistry [24], Arduino IDE and BLE libraries were used to successfully set up data reading systems. Using Arduino IDE, the library of the MPU6050 sensor [25] was easily installed to read IMU data so that the development environment needed for the sensor tag became more user-friendly and convenient. Fig. 3 exhibits the output framework of the Generic Attribute Profile (GATT) with the sensor tag set as a peripheral device of BLE.

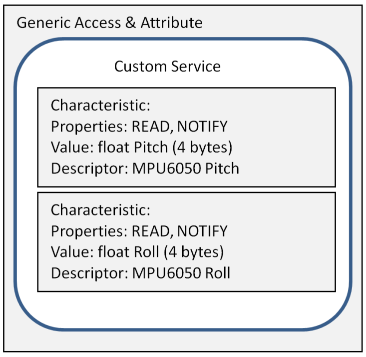

Fig. 3. Structure of GATT transaction

The firmware program in Arduino IDE is fairly streamlined. Before using the sensor tag, the MPU6050 accelerometer needs calibration. The calibration program developed by Ródenas [26], in which the sensor tag is horizontally placed, was used. After 1100 items of raw accelerometer data were read, the average of the last 1000 items served as the offsets. From the Arduino IDE serial monitor, the offsets of the three axes were written down and applied to develop firmware that sent pitch and roll angles via BLE.

Once the firmware was developed, the MPU6050 procedure, getMotion6, was used to obtain raw 3-axis data from the accelerometer at a sample rate of 50 Hz, from which the previously obtained offsets were subtracted. Then, Eqs. (1) and (2) below were employed to derive the pitch and roll angles, respectively [27]. The radian units [$-\pi/2$, $\pi/2$] were then mapped to degree units [-90°, 90°]:

$$Pitch = \arctan\left[\frac{A_x}{\sqrt{(A_y)^2 + (A_z)^2}}\right] \times \frac{180}{\pi}. \quad \textbf{(1)}$$

$$Roll = \arctan\left[\frac{A_y}{\sqrt{(A_x)^2 + (A_z)^2}}\right] \times \frac{180}{\pi}. \quad \textbf{(2)}$$

In Eqs. (1) and (2), Ax, Ay, and Az respectively denote the acceleration values in the directions of the X, Y, and Z axes. Fig. 4 shows the pitch and roll of head motions. After the conversion, BLE procedures [24] were used to send 4 bytes of pitch values and 4 bytes of roll values.

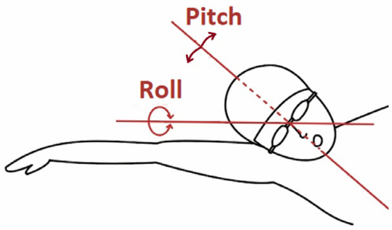

Fig. 4. Pitch and roll angles

2.3 Sensor Placement

The original design had no external antenna. To attach an external antenna for use in an aquatic environment, the circuit layout of the sensor tag that had been made public was examined to find the antenna circuit [21]. As shown in Fig. 5, the paint originally covering the antenna was scraped off and welded onto a 20-cm soft antenna.

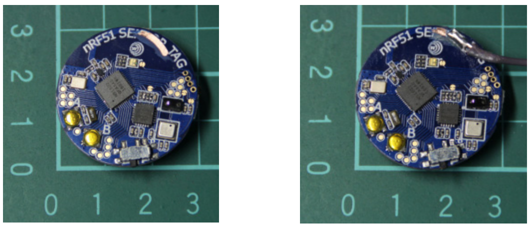

Fig. 5. Soldering an external antenna to the sensor tag

Then the sensor tag was placed in a waterproof bag, which was fixed to the head and aligned with the upper edges of the ears using the goggle straps, as shown in the upper left image in Fig. 6. The hole that the antenna extended out from was tied tightly with a rubber band and then fixed with waterproof tape. The end of the antenna was tied to a 3cm×3cm×3cm piece of Styrofoam so that the antenna would float on the water surface. The device was worn inside the swimming cap, as shown in the upper right image in Fig. 6. A white silicone swimming cap was chosen so that the LED light on the sensor tag could be visible to indicate the system status during operation. A small hole was created in the middle of the swimming cap for the antenna and Styrofoam to feed through, as shown in the bottom image of Fig. 6.

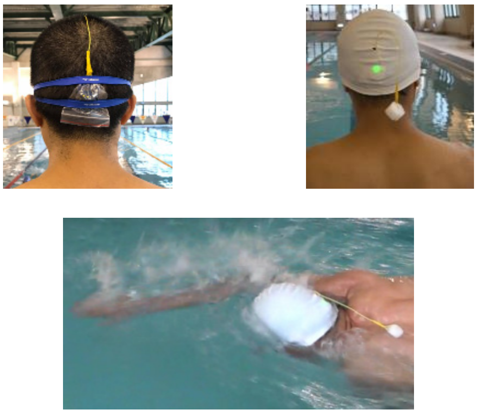

Fig. 6. Upper left: protection with waterproof bag; upper right: placement in swimming cap; bottom: conditions during swimming

2.4 Android Application

The software system developed in this study used an Android mobile phone as the central device of BLE to receive pitch and roll data from the peripheral device, e.g., the sensor tag. On the screen, a line graph is drawn so that the poolside coach or sports scientist can see the data in real time. Finally, the received data can be stored within the memory of the Android mobile phone in the format of a csv file and uploaded to Google Drive, where it can be post-processed online using Google Sheets or downloaded to a computer and then post-processed using Microsoft EXCEL.

Fig. 7 exhibits the system framework of the Android application. Google's Android official example of BLE [28, 29] was modified to read streamed data of the sensor tag. The program was also linked to the MPAndroidChart library developed by Jahoda [30] to display real-time line charts. With a sample rate of 50 Hz, a CR2032 battery was used to send a total of 8 bytes of float data containing pitch and roll angles. To reduce power consumption, the LED light on the sensor tag flashed green once per second to indicate normal data transmission. With these settings, the sensor tag can work continuously for over three hours.

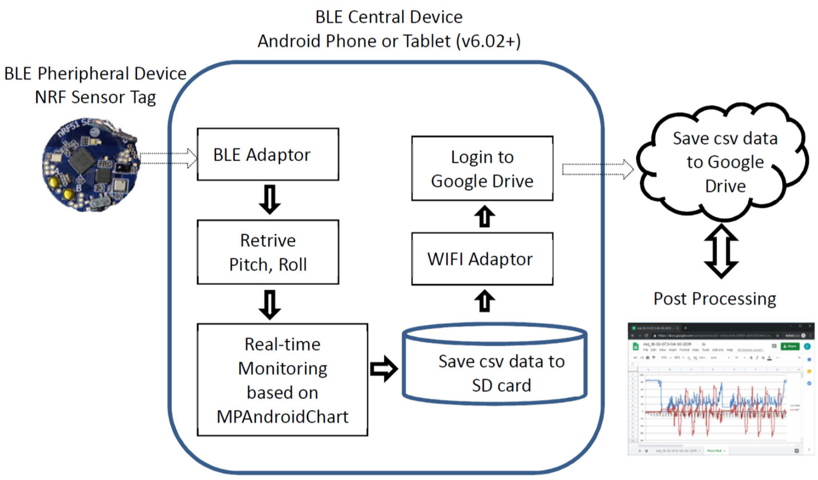

Fig. 7. Proposed mobile real-time swimming monitoring system

2.5 Data Acquisition

A case study for recreational environment was conducted to examine the feasibility of the sensor tag firmware and the Android mobile device software previously described. Two swimmers volunteered for this case study. Swimmer A was a 50-year-old recreational swimmer who had four years of front crawl swimming experience, and Swimmer B was a 42-year-old swimming coach in a rural area. Once a semi-professional swimmer, Swimmer B had gotten into the top three places in a national triathlon competition and in fact was Swimmer A's coach. In a 25-m pool, the two swimmers first did a warm-up for 100 m. They were then asked to swim three 50-m laps using front crawl at a swimming speed they were comfortable with. Using purposive sampling, data extracted from the lap that the swimmers felt was closest to their normal swimming patterns as the baseline for comparison. While Swimmer A swam, Swimmer B observed the sensor tag values on a mobile phone beside the pool, and counted the number of breaths that Swimmer A took. While Swimmer B swam, Swimmer A counted the number of breaths that were taken.

The head pitch and roll data were captured by the sensor tags placed on the two swimmers. The pitch and roll data were sent to an Android mobile device via BLE, as shown in Fig. 7. Aside from enabling poolside observations of swimmer head motions in real time, the data can also be stored in the SD card of the mobile device or uploaded to Google Drive for post analysis. Using the data provided by the sensor tags, the pitch and roll angles as well as the breathing patterns of the two swimmers were analyzable.

3 Results and Discussion

The sensor tag can detect the timing of breathing, and based on the angle and peak values of roll, it is possible to verify whether a swimmer takes breaths to the left or to the right and how many breaths a swimmer takes during each lap (50 m). After the experiment, the information downloaded and stored in the mobile device or on Google Drive was used to analyze breathing patterns.

3.1 Characteristics of Head Movements and Breathing Patterns Retrieved from IMUs

Fig. 8 shows the line figure obtained from the bilateral breathing of Swimmer A during one lap (50 m) of a 25-m pool with a simple turn at 25 m. The vertical axis shows the angle degrees, and the horizontal axis shows the sampling time. The solid and dashed lines indicate the changes in the roll and pitch angles, respectively.

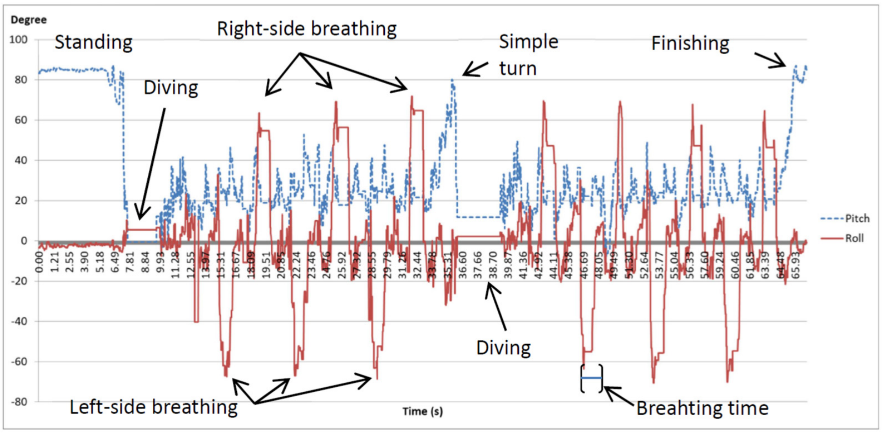

Fig. 8. Pitch and roll angles and description of important swimming patterns for Swimmer A

The pitch/roll curves of Swimmer A in Fig. 8 show that excluding possible breathing behaviors during the simple turn and the finishing. Swimmer A took a total of 13 breaths, which was consistent with the number observed by Swimmer B and the number counted by Swimmer A himself. This demonstrates that the peak values which appear in the roll angle during breathing can effectively indicate when and which side a swimmer takes a breath and what the breathing angle is. Fig. 9 displays the line graph from the front crawl swimming of Swimmer B, in which Swimmer B made a flip turn at 25 m.

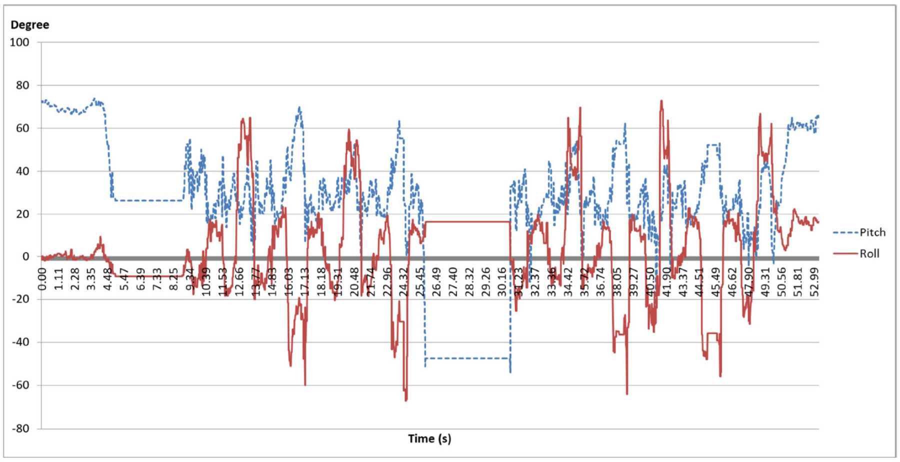

Fig. 9. Pitch and roll angles of Swimmer B

As can be seen in Fig. 8 and Fig. 9, the breathing patterns of the two swimmers differ somewhat, but their roll angles were all significantly greater when they were taking a breath than when they were not. Psycharakis and Sanders [31] mainly measured roll angles of the body, and their results also indicated that the roll angle of the body is significantly greater when the swimmer is taking a breath than when the swimmer is not. Thus, their results were similar to ours. The curves from Swimmer B in Fig. 9 show two obvious peak values each time a breath is taken. A portion of Fig. 9 was extracted in Fig. 10 to explain this further. Comparison with the video taken during the experiment and an interview with Swimmer B regarding his stroke and breathing methods revealed that the first roll peak was a result of the entry and catch, the trough showed the head motions resulting from the push and glide, and the final highest roll peak, while pitch angle is the lowest, was the actual breathing motion. As shown in Fig. 8, Fig. 9, and Fig. 10, the semi-pro Swimmer B had better front crawl strokes than Swimmer A, because Swimmer A was already lifting his head and preparing to take a breath during the catch phase and maintains a relatively wide roll angle during the push and glide phases, which produced drag.

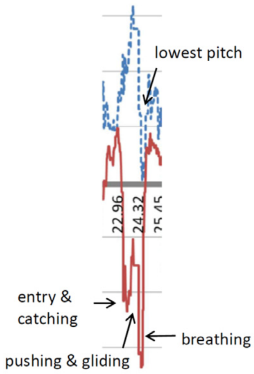

Fig. 10. IMU setup on back of head represents phases of arm movement.

As the roll angles during breathing were already obvious, A FIR low-pass filter was adopted to enhance the peak value information during breathing to extract the features. Mooney et al. [8] also suggested that a low-pass filter was able to enhance some of the swimming posture features but that there was no single low-pass filter or fixed parameters that could meet all feature extraction needs. In this study, it was found that the peaks of breathing features were still apparent after applying a low-pass filter with a cut-off frequency of 2.5 Hz, as shown in Fig. 11. The roll and pitch angle values processed using a low-pass filter with a cut-off frequency of 2.5 Hz were r_t (t=1…n) and p_t (t=1…n). Then Eqs. (3) and (4) were utilized to normalize r_t into Z-score Zr_t and Eqs. (5) and (6) to normalize p_t into Z-score Zp_t. Fig. 11 displays the Zr_t and Zp_t curves of Swimmer A, while Fig. 12 shows the Zr_t and Zp_t curves of Swimmer B.

$$S_r = \sqrt{\frac{\sum_{t=1}^{n}(r_t - \overline{r})^2}{n-1}}. \tag{3}$$

$$Zr_t = \frac{r_t - \overline{r}}{S_r}, t = 1 \ldots n. \tag{4}$$

$$S_p = \sqrt{\frac{\sum_{t=1}^{n}(p_t - \overline{p})^2}{n-1}}. \tag{5}$$

$$Zp_t = \frac{p_t - \overline{p}}{S_p}, t = 1 \ldots n. \tag{6}$$

$\overline{r}$ and $\overline{p}$ represent the mean roll and pitch angles during one lap of front crawl swimming, and S_r and S_p denote the standard deviations of the roll and pitch angles.

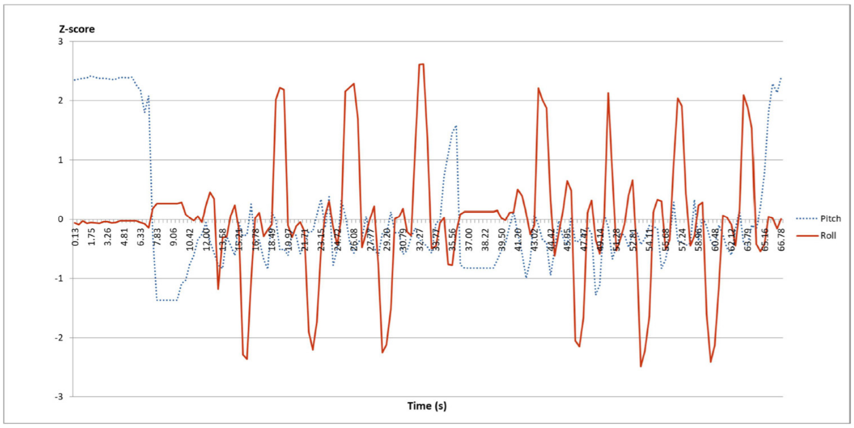

Fig. 11. Swimmer A's Z-scores of low-pass filtered roll angles are over ±1.96 standard deviations when breathing

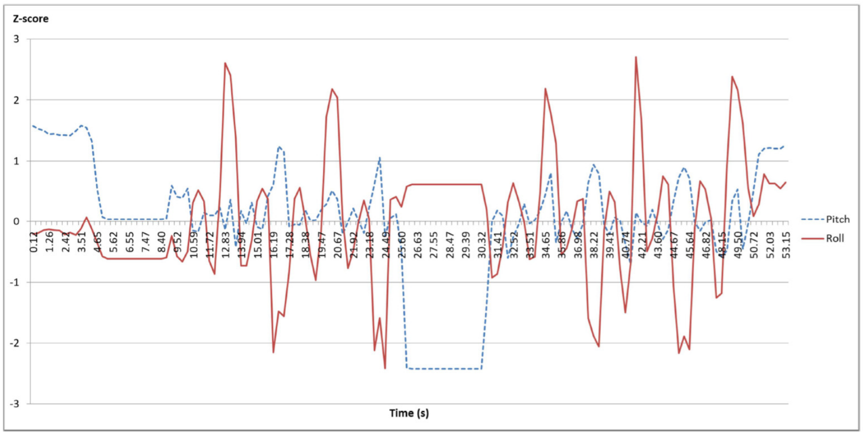

Fig. 12. Swimmer B's Z-scores of low-pass filtered roll angles

As can be seen, the Z-scores of low-pass filtered roll angles for breathing to the right are statistically significantly greater than 1.96, whereas the Z-scores of roll angles for breathing to the left are statistically significantly less than -1.96. It is worth noting that some of the details of pitch and roll during different phases of a stroke are lost in the low-pass filtered IMU feature values in Fig. 11 and Fig. 12 when they are compared to the unfiltered raw values in Fig. 8, Fig. 9, and Fig. 10. Therefore the accurate analysis of swimmer breathing patterns should not be only based on filtered information alone but that the raw data should be included as well. This finding is supported by the discussion made by Mooney et al. [8] in the signal filtering section of their review.

3.2 Algorithm for Detecting Head Position and Breathing Patterns

Based on the filtered information, a detection program for head position and breathing patterns was implemented on the Android platform. This application is able to calculate the numbers and angles of breaths taken to the left and to the right during front crawl swimming. The pseudocode algorithm for the detection of head position and breathing patterns to the right is as shown below. Some of the parameters in this algorithm can easily be modified to detect breathing to the left.

```
Line Algorithm for Detecting Head Position and Breathing Patterns
  1  FUNCTION right-side_breathing_and_angles
  2    Clear all variables
  3    Define R_t as an array, t=1...n
  4    Define Right-Side_Breathing_TimeStamp as a list
  5    Define Right-Side_Breathing_Angle as a list
  6    Define Right-Side_Breathing_Pitch_Angle as a list
  7    Let Z-Threshold = 1.96
  8    Assign low-pass filtered roll angles to r_t
  9    Normalize r_t to z-scores Zr_t, t=1...n
 10    For each t, t=1...n
 11      If Zr_t ≥ Z-Threshold then
 12        R_t = 1
 13      Else
 14        R_t = 0
 15      End of if
 16    End of for
 17    For R_t, t=1...n
 18      Find a segment of consecutive ones
 19      Increase Right-Side_Breathing_Count
 20      Let i = Right-Side_Breathing_Count
 21      Right-Side_Breathing_TimeStamp(i)= t
 22      Right-Side_Breathing_Angle(i) = r_t(t)
 23      Right-Side_Breathing_Pitch_Angle(i) = p_t(t)
 24      If (i>1) then
 25        currentTime = Time(Right-Side_Breathing_TimeStamp(i))
 26        previousTime = Time(Right-Side_Breathing_TimeStamp(i-1))
 27        If (currentTime - previousTime < 1) then
 28          Decrease Right-Side_Breathing_Count
 29         Right-Side_Breathing_Angle(Right-
               Side_Breathing_Count)=[r_t(i) + r_t(i-1)]/2
 30         Right-Side_Breathing_Pitch_Angle(Right-
               Side_Breathing_Count)= [p_t(i) + p_t(i-1)]/2
 31        End of if
 32      End of if
 33    End of for
 34    Return Right-Side_Breathing_Count
 35    Return Right-Side_Breathing_Angle
 36    Return Right-Side_Breathing_Pitch_Angle
 37  End of FUNCTION
```

Line 2 to 9 of the proposed algorithm describe the initial work. On line 7, the initial threshold of Z-score is set to 1.96 because it indicates a statistically significant change if a Z-score is less than -1.96 or larger than +1.96. Then on line 9, the roll angles r_t are normalized to Zr_t. Therefore, if a normalized roll angle Zr_t is less than -1.96 or greater than +1.96, the roll angle is significantly changed, which indicates a breathing movement. The statistically significant movements are found by the segment of algorithm from line 10 to 16. Line 17 to 23 of the algorithm count the number of breaths, identify the moments of breaths, and store the values of roll and pitch angles.

As with previous observations of the curves from swimmers, an additional peak value appears in the roll angle during the catching phase. Furthermore, breathing does not take place twice within a second in bilateral breathing during front crawl swimming. Thus, in the code segment of the algorithm from line 24 to 32, peak values within a second of each other were considered a single breath rather than two breaths on the same side, thereby preventing misjudgment. The final outputs of this algorithm, which are illustrated from lines 34 to 36, are the number of breaths taken to the right as well as the roll and pitch angles of each breath. For breathing to the left, only a few variables in this algorithm need to be modified.

3.3 Results of Applying the Proposed Algorithm

Derived from the algorithms, Swimmer A took 7 breaths to the right and 6 breaths to the left, thereby presenting a total of 13 breaths. The number calculated by the algorithm was identical to the number observed by Swimmer B and the number counted by Swimmer A himself. Applying the algorithms for detecting Swimmer B's breathing counts shown in Fig. 12, the algorithms indicated that Swimmer B took 5 breaths to the right and 4 breaths to the left, which was also consistent with the number observed by Swimmer A and the number counted by Swimmer B himself.

Compared to the semi-professional Swimmer B, Swimmer A displayed greater breathing angles to the left and to the right as well as more breaths. Because Swimmer A swam less efficiently than Swimmer B, the bow wave effects created at the head were also poorer. Swimmer A thus requires greater roll angles to breathe and a higher breathing frequency than Swimmer B. The mean angles of breathing to the left and to the right show that Swimmer A had better breathing symmetry than Swimmer B, and the standard deviations indicated that the variance in breathing angles of Swimmer A was smaller than that of Swimmer B. In other words, Swimmer A was able to exert more control over his roll than Swimmer B. The analysis in Table 1 also shows that our roll angles were consistent with the study results obtained by Payton et al. [32] in that the maximum roll angle during breathing was around 66°±5°. However, our data processing time and installation costs are much shorter and lower than those of their camera analysis method.

Table 1. Descriptive statistics of pitch and roll angles for swimmers

Swimmer	Pitch/Roll	Average	# of Breaths	Time(s)
Swimmer A	Right Pitch	44.429	7	3.204
	Left Pitch	42.808	6	7.657
	Right Roll	67.497	7	3.586
	Left Roll	67.544	6	2.981
Swimmer B	Right Pitch	41.676	5	6.250
	Left Pitch	58.970	4	5.790
	Right Roll	65.996	5	5.946
	Left Roll	61.850	4	4.957

When coaches are giving instruction on front crawl swimming, they should pay attention to the swimmer's head pitch data. The position of the head is a crucial factor of swimming performance. If the pitch of the head is too high, it will increase the drag [20], and therefore, the position of the head has a profound impact on the performance of front crawl swimming [32]. The pitch angles in Table 1 show the differences between Swimmer A and Swimmer B. The former presented a greater pitch than the latter when taking a breath to the right, but the standard deviation of the pitch was smaller. In contrast, the former presented a much smaller pitch than the latter when taking a breath to the left, but the standard deviation of the pitch was much higher. The line graphs in Fig. 8 and Fig. 9 also show that when Swimmer A took a breath, he tended to raise his head first and then roll his head. This raising of the head in advance made up for the insufficient roll angle needed for adequate breathing. Thus, the roll angle of the head after a breath was taken was somewhat smaller, but raising the head before breathing increased the drag. In contrast, as sampled in Fig. 10, Swimmer B took breaths when the pitch was lowest, so the breathing motion was more natural and decreased the drag. When breathing to the left, however, Swimmer B used a higher pitch to make up for the smaller roll angle. Clearly, the data captured by the sensor tag can provide coaches and swimmers with objective reference data, show the advantages and disadvantages in the posture of the swimmers, and help swimmers improve their swimming technique.

3.4 Comparison with Related Works

In sum, the major differences between the proposed work and other related ones can be divided into two dimensions: method of wireless data transmission and a feasible algorithm to detect breathing pattern and head position during front crawl swimming.

This study employed open-source hardware and software to develop an Android application that wirelessly associates with an IMU through standard Bluetooth 4.0 protocol, and so it provides better usability than similar set ups that used non-standard wireless protocol to transmit data [10-12, 15]. For storing and preserving swimming data, a swimmer's data can be instantaneously displayed on and stored in the mobile device while observing front crawl swimming, so there is no need for an SD card. In addition, all data in a mobile device can be uploaded to the cloud storage for backup and post analysis. Most related works store data in an SD card, or users have to retrieve data from a computer after finishing swimming [6]. Clearly, compared with other related works, the proposed work has advantages with respect to instantaneous data visualization, data transmission, data storage, and data preservation.

With regard to front crawl swimming, even though the research goals are very close to the research of Pansiot et al. [6], our proposed approaches are quite different. Not only approaches of real-time data transmission and visualization are proposed, but also an automatic detection algorithm of breathing patterns is developed. Usually, coaches need to intuitively distinguish breathing patterns from overwhelming swimming data in order to do further statistical analysis. Our proposed algorithm is more feasible by applying FIR low-pass filtered data to enhance peak values of pitch/roll angles, and then automatically retrieve breathing patterns such as number of breaths, pitch angles, and roll angles. Since these breathing patterns are important factors for swimming performance, the proposed detection algorithm is a novel method for assessing swimming actions.

4 Conclusions and Recommendations

To conclude, the proposed system can display and store the pitch and roll angle data of the head during front crawl swimming in real time. The installation costs of the proposed system are much lower than conventional video-based devices, and it can be used to improve the swimming technique of swimmers without a professional experimental environment. Not only are the devices affordable, the data can also be uploaded to Google Drive for back up and using cloud applications to conduct post analysis. Moreover, the major finding is that the proposed algorithm can facilitate the analysis of head angles and breathing patterns during front crawl swimming and thereby help swimmers improve their swimming technique. The developed system can thus provide important feedback to the swimming community.

Since the study involved only one IMU set on the back of the head, the data obtained from the IMU cannot be analyzed for the detailed movements of leg kicks and arm orientations. There is a need for adopting multiple IMUs to retrieve various information of swimmer movements. However, mobile devices are limited in computational and communicational capacity. Transmitting information from multiple IMUs to a mobile device over Bluetooth protocol in the same manner as the present study may not be reliable. There thus will be two dimensions that might be addressed by future researchers: (A) Future research could assess the feasibility of capturing whole-body mobility of a swimmer in an aquatic environment with multiple wireless IMUs on different body parts. (B) The feasibility of wireless transmission of data retrieved from multiple IMUs via other standard protocols, such as Wi-Fi, to a more powerful device should be assessed. The device could be able to store swimming data and simultaneously display information to swimmers or coaches.

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