Swimming Stroke Kinematic Analysis with BSN

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***Abstract*—The recent maturity of body sensor networks has enabled a wide range of applications in sports, well-being and healthcare [1]. In this paper, we hypothesise that a single unobtrusive head-worn inertial sensor can be used to infer certain biomotion details of specific swimming techniques. The sensor, weighing only seven grams is mounted on the swimmer's goggles, limiting the disturbance to a minimum. Features extracted from the recorded acceleration such as the pitch and roll angles allow to recognise the type of stroke, as well as basic biomotion indices. The system proposed represents a non-intrusive, practical deployment of wearable sensors for swimming performance monitoring.**

***Keywords*-swimming biomechanics; Body Sensor Networks (BSN); sport monitoring**

I. Introduction

With increasingly small margin between medallists in short distance swimming, the use of technology for detailed biomotion analysis and technical refinement is playing an important role in training. Indeed, the use of video cameras or sensors for capturing, modelling and fine-tuning swimming strokes has become a common requirement for elite swimmers [2].

The traditional gold-standard methods for swim motion analysis are mostly video-based. This is typically performed by recording a raw video sequence [3], [4], sometimes with reflective markers attached to the swimmer [5], and tracking the points of interest using specific software packages [6], [7]. The points tracked typically include articulations such as the wrist, elbow and shoulder [8]. This process is difficult to fully automate and tends to be error-prone [9]. Automated systems for stroke recognitions have also been attempted [10]. Although this can provide the swimmers and coaches with detailed motion analysis, it requires time consuming system installation and calibration [11] and intensive data post-processing. In particular, bubbles due to water turbulence represent a significant issue for underwater tracking [8].

As an alternative, wearable sensors do not require complicated setup in the swimming pool. They are also more swimmer-centric, *i.e.* each swimmer wears his/her own sensor which is independent from the others.

In this paper, we demonstrate that a single, lightweight sensor can be used for swimming motion monitoring to capture basic indices such as laps, strokes, as well as biomotion indices. We will demonstrate its use for detailed motion analysis for exemplar techniques using front crawl and breaststroke.

II. Related work

Early work was performed by Ohgi [8], who developed wrist-worn sensors containing an accelerometer or a gyroscope. The author was able to demonstrate the effect of fatigue on swimming technique. A video-based technique was also employed to augment the wearable sensor data for more detailed analysis.

The papers by Bächlin *et al.* (SwimMaster) [12], Davey *et al.* [13] and Khoo *et al.* (SWiSS) [14] are the most related to our study. Bächlin *et al.* [12] have carried out extensive validation of multiple body-worn accelerometers (lower and upper back, wrist). Motion analysis is mainly performed based on pitch and roll angles derived from the accelerometers. They have also proposed a real-time feedback to the swimming goggles through three different modalities: visual (LED), acoustic (piezo beeper) and haptic (vibration motor). Davey *et al.* [13] rely on a single back-worn accelerometer, which is proven to be less intrusive despite its relative large size (20 cm). Khoo *et al.* [14] developed a hybrid system composed of a wearable accelerometer and an underwater camera. The sensor is placed at the back of the head and relatively unobtrusive. In [12] and [13], both stroke style and count can be performed. Other indices include push-offs, distance, split time and speed estimation, whereas in [14], the acceleration generated by each stroke is visualised on a screen off-line. A comparison of the placement of the sensors mentioned here-above along with the features they provide is summarise in Table I.

TABLE I
PLACEMENT AND FEATURES EXTRACTED FROM PREVIOUS WORK.

	Trunk	Head	Arms
Body angles	[12]		
Velocity	[12]		[12]
Stroke count	[13]	[14]	[12]
Raw acceleration		[14]	[8]

A comparison of accelerometer- and video-based methods is proposed by Callaway *et al.* [2]. The authors demonstrated some shortcomings of accelerometer-based methods, but remained confident that inertial MEMS sensors can provide significant improvement for swimming biomechanics analysis.

III. System architecture

A. Hardware

In this study, we aim at using a single miniaturised sensor in order to reduce the discomfort experienced by the swimmer. We have chosen to place the sensor on the swimmer's head, as for certain swimming styles, *e.g.* front crawl, the head angle can also provide information about breathing patterns. We use a modified version of the ear-worn Activity Recognition (e-AR) sensor originally developed by Lo *et al.* [15]. Its architecture is based on a Nordic nRF24E1 with built-in 2.4GHz RF transceiver, 2MB memory, and an analogue-digital converter retrieving data from a three-axis accelerometer. The sensor can either transmit data in real-time to a base station or store the signal on-board. It is lightweight (7 grams) and causes minimal disturbance to motion and fluid dynamics.

Fig. 1. The modified waterproof ear-worn Activity Recognition (e-AR) sensor mounted on the swimmer's goggles.

The sensor is waterproofed using a rubber latex skin, as illustrated in Figure 1. Because it would not be practical to transmit the measured acceleration data in real-time to a base station, the sensor is programmed to record data in its internal memory, which can be downloaded through the wireless interface after each length or the swimming session. The sensor was configured to record the three-axial acceleration at 50 Hz.

B. On-body sensor placement

The most popular sensor placements for swimming motion monitoring include the lower and upper back [12], [13], head [14], wrists [8], [12] and ankles [16]. Table II summarises the relevant features that can be calculated from the sensor depending on its placement for the four main swimming strokes: front crawl (FC), backstroke (BaS), breaststroke (BrS), butterfly (Bf). Because it is intended to derive the overall motion as a minimum requirement, the trunk and head placements were most promising for all strokes. Its integration with the swimming goggles also presents a practical deployment format, therefore the head was eventually chosen. Preliminary experiments with watch-mounted sensors have also been carried out.

TABLE II
FEATURES THAT CAN BE DERIVED FOR SEVERAL SENSOR PLACEMENTS.

Stroke	Feature	Trunk	Head	Arms	Legs
All	Lap count & timing	++	++	++	++
All	Overall momentum	++	++	-	-
FC	Stroke count	+	+	++	-
BaS	Stroke count	-	-	++	-
BrS, Bf	Stroke count	++	++	++	++
FC, BaS	Body roll	++	+	-	-
FC	Breathing patterns	+	++	-	-
FC, BaS	Arm anti-symmetry	-	-	++	-
BrS, Bf	Arm symmetry	-	-	++	-
FC, BaS	Leg anti-symmetry	-	-	-	++
BrS, Bf	Leg symmetry	-	-	-	++

IV. EXPERIMENT

A. In-pool experiment

In this study, the newly modified sensor was attached on the swimmer's goggles, next to the ear. The swimmer was asked to perform three main different strokes: front crawl (FC), breaststroke (BrS) and backstroke (BaS). Further variations were required for the front crawl. The swimmer was asked to breath to the right every two or four strokes (FC-2r and FC-4r respectively), to the left every two or four strokes (FC-2l and FC-4l respectively), and alternatively on either sides every three strokes (FC-3).

Simple and flip turns were performed between laps. During a simple turn, such as required for breaststroke and butterfly, the swimmer touches the wall with both hands, turns around (vertical axis rotation) and pushes against the wall with his/her legs. Front crawl and backstroke wall push-offs can be performed with a flip turn (or tumble turn), where the swimmer flips upside-down (horizontal axis rotation) before the push-off.

The data was then retrieved from the sensor using the wireless link and post-processed on a PC.

B. Feature extraction

The raw acceleration data is first filtered with a low-pass filter at 5 Hz.

The swimmer's head motion has six degrees of freedom (DOF), *i.e.* three DOF for the position and three DOF for the rotation. Because the accelerometer is worn by the swimmer, its coordinate system will be subject to the body rotation. Therefore, each of the three acceleration components measured by the accelerometer is actually a consequence of both position and rotational motions. Therefore, it is theoretically difficult to recover either the position or the orientation from the accelerometer alone in general cases. It should be noted that MEMS accelerometers measure the motion relative to free-fall. Therefore, an accelerometer left static measures the acceleration induced by the Earth gravity. The acceleration $a_{acc} = (a_{acc,x}, a_{acc,y}, a_{acc,z})$ measured by the accelerometer depends on the actual acceleration in a geocentric coordinate system $a_{geo} = (a_{geo,x}, a_{geo,y}, a_{geo,z})$, the orientation of the body defined by the yaw (ψ), pitch (θ) and roll (ϕ) angles (illustrated in Figure 2), and the gravity $G = (0, 0, -g)$:

$$a_{acc} = R(\psi, \theta, \phi)(a_{geo} + G) \tag{1}$$

Using the Euler angles (Tait-Bryan convention [17]) to

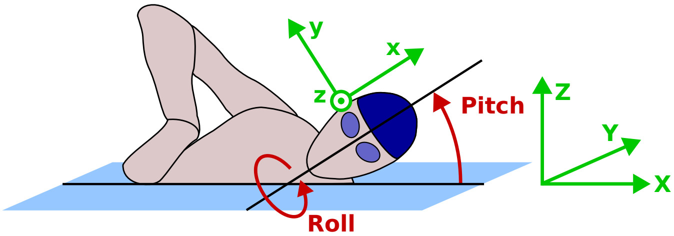

Fig. 2. The geocentric coordinate system (X, Y, Z), the accelerometer coordinate system (x, y, z) and the pitch (θ) and roll (ϕ) angles estimated in this study.

determine the rotation matrix $R(\psi, \theta, \phi)$, we can derive:

$$\begin{aligned} a_{acc,x} &= \cos\psi\cos\theta a_{geo,x} \\ &\quad - \cos\theta\sin\psi a_{geo,y} \\ &\quad + \sin\theta(a_{geo,z} - g) \end{aligned} \tag{2}$$

$$\begin{aligned} a_{acc,y} &= (\cos\psi\cos\phi\sin\theta + \sin\psi\sin\phi)a_{geo,x} \\ &\quad + \cos\theta\cos\phi a_{geo,y} \\ &\quad - \cos\theta\sin\phi(a_{geo,z} - g) \end{aligned} \tag{3}$$

$$\begin{aligned} a_{acc,z} &= -(\cos\psi\sin\phi + \cos\psi\cos\phi\sin\theta)a_{geo,x} \\ &\quad + (\cos\phi\sin\psi\sin\theta + \cos\psi\sin\phi)a_{geo,y} \\ &\quad + \cos\theta\cos\phi(a_{geo,z} - g) \end{aligned} \tag{4}$$

In order to extract meaningful information from the acceleration measured by the accelerometer, further assumptions on the motion must be verified. Typical assumptions include a low acceleration a_{geo} compared to the gravity g and known rotation angles. It should be noted that the literature exhibits a number of cases where one of these assumptions is chosen in an implicit manner without further justification.

1) Low acceleration assumption: In many cases, the acceleration in the geocentric coordinate system is negligible compared to the gravity, as assumed implicitly in [13] and explicitly in [12]. In our experiment, the overall measured acceleration was between $5.9ms^{-2}$ and $13.7ms^{-2}$ (*i.e.* $g \pm 40\%$). In this case, *i.e.* $g \gg \|a_{geo}\|$, we can simplify the equations 2 to 4 and estimate:

$$a_{acc} = -g \begin{bmatrix} \sin\theta \\ -\cos\theta\sin\phi \\ \cos\theta\cos\phi \end{bmatrix} \tag{5}$$

Therefore, the pitch and roll angles can be derived from the measured acceleration as follows:

$$\theta = -\arcsin\frac{a_{acc,x}}{g} \tag{6}$$

$$\phi = -\arctan\frac{a_{acc,y}}{a_{acc,z}} \tag{7}$$

By using the function '$\mathrm{atan2}(y, z)$' in place of '$\arctan(y/z)$' in Equation 7, it is possible to enforce:

$$\theta \in [-\frac{\pi}{2}, \frac{\pi}{2}] \tag{8}$$

$$\phi \in [-\pi, \pi] \tag{9}$$

Furthermore, the acceleration is first normalised to g in an attempt to reduce the artefacts when the low acceleration assumption does not hold.

In can be noted that the yaw angle (ψ) does not appear in Equation 5. As a consequence, the orientation of the swimmer in the horizontal plane cannot be determined in that way. A magnetometer [17], as used in Chan's lap counter [18], or a gyroscope would be required for this purpose. This makes sense intuitively, since the accelerometer left static is in fact measuring its rotation with respect to the vertical axis.

2) Known rotation assumption: Another assumption consists of assuming that some angles are known (typically multiples of $\pi/2$). In [14], the overall measured acceleration is compared for the left and right strokes in order to establish asymmetric motion. Although not explicitly mentioned in the paper, it seems that the head is expected to keep a constant orientation during the stroke.

It should be noted that [8] presents results derived directly from the accelerometer values, without further assumptions.

3) Feature choice: In this paper, it was chosen to rely on the *low-acceleration* assumption rather than the *known rotation* for two main reasons. First, the recorded data shows that the first assumption holds relatively well, whereas the second is harder to enforce. Secondly, extracting the main body angles appears to make more sense than the overall acceleration from a coaching perspective. Indeed these angles provide a direct observation of some of the swimmer's motion key biomechanics parameters, whereas the acceleration is the consequence of a large number of biomechanics and fluid dynamics parameters. Therefore, it is easier to implement corrections on a training program from the body angles.

V. Results

A. Basic dynamic indices

Simple turns and flip turns (sometimes referred to as 'tumble turn') can be detected easily, as illustrated in Figure 3. Once the turns and wall push-offs are detected, the laps can be counted and timed.

The different strokes illustrated in Figures 3 (breaststroke), 5 (backstroke) and 6 (front crawl), can be easily distinguished from each other by using the derived pitch and roll angles, as illustrated in Figure 4.

The *k*-means [19] algorithm was used to cluster the different strokes in an unsupervised fashion. The assignment step was based on the Mahalanobis distance [20] in order to compensate for a significant difference of variance in the pitch and roll angles. The discrimination lines derived from the algorithm are show in Figure 4.

Strokes can be counted for the front crawl and breaststroke. The minima and maxima of the roll angles were detected for this purpose. In the case of the front crawl, the dominant extrema were also dissociated from the minor ones, as they indicate a large roll amplitude associated with the breathing actions, as illustrated in Figure 6.

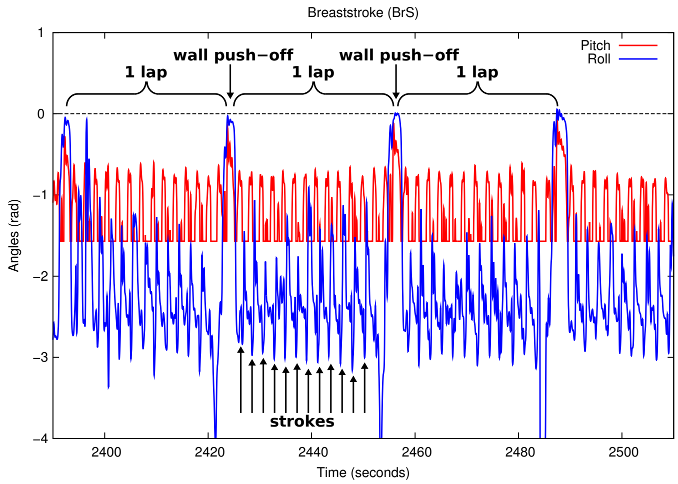

Fig. 3. Pitch and roll angles as measured during a breaststroke training session. The strokes and wall push-offs are obvious. Note the saturation of the pitch angle, as a result of the low-acceleration assumption.

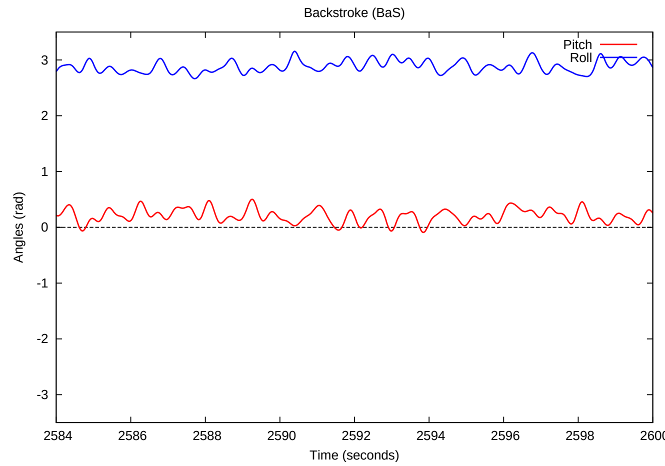

Fig. 5. Pitch and roll angles as measured during backstroke. Both angles are relatively constant due to the low motion amplitude in this stroke. The roll angle value is close to π, expressing that the swimmer is "upside-down" as compared to the other swimming strokes.

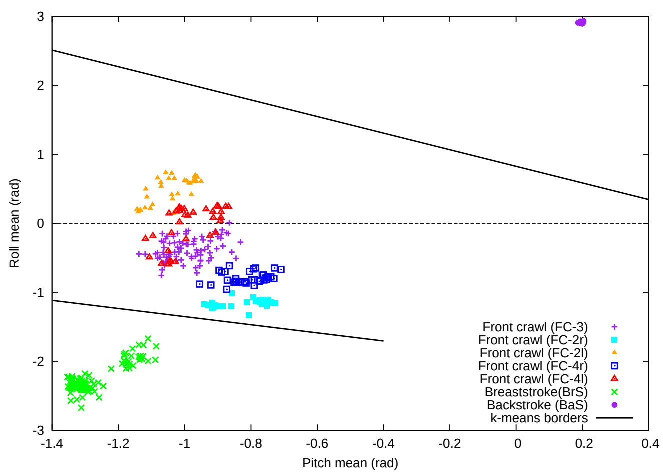

Fig. 4. Pitch mean angle against roll mean angle for several stroke types. All main classes are well separated by *k*-means clustering (note the backstroke on the top right corner). The front crawl variations are slightly interlaced, but nevertheless distinct and ordered in the following sequence when the roll angle increases: FC-2r, FC-4r, FC-3, FC-4l, FC-2l. The symmetry in this order reflects how much the swimmer tends to roll to a given side. It can also be noted that the angles show more variability when breathing on the left side.

B. Biomechanical indices

1) Front crawl biomechanics: The front-crawl stroke biomechanical arm cycle can be decomposed into five phases [21], although simpler models are often used [3], [4]:

1) **Entry**: alignment of the arm with the surface of the water (glide or stretch).
2) **Downsweep**: non-propulsive motion during which the arm goes down until the "catch".
3) **Insweep (or pull)**: propulsive motion of the arm up to the shoulder level.
4) **Upsweep (or push)**: propulsive motion of the arm past the shoulder until the water exit.
5) **Recovery**: aerial time between the exit and the next water entry.

2) Breathing patterns: Whilst a continuous body roll is expected from the swimmer [3], [21], this roll is accentuated to permit breathing. This breathing roll can be performed on either side, leaving the choice to breath always on the same side or to alternate in between. Whilst bilateral patterns are commonly taught, unilateral ones are often preferred during competition [4] in order to make the stabilisation process easier. The breathing patterns can be extracted from the signal, as illustrated in Figure 6.

Vezos *et al.* [3] evaluated the effect of breathing on the front crawl stroke. They found that the duration of the underwater phase of the stroke was significantly longer when breathing, and this is mostly due to longer glide and downsweep phases. The average durations of the front crawl strokes for a given swimmer are given in Table III. It is clear from this table that the breathing actions indeed increase significantly the stroke duration for all breathing cycle patterns.

TABLE III
INFLUENCE OF BREATHING ACTIONS ON THE FRONT CRAWL STROKE DURATION. AVERAGE AND STANDARD DEVIATION OF THE STROKE DURATIONS ARE GIVEN IN MILLISECONDS.

Stroke	**Right**		**Left**		**Overall**	
	Regular	Breath	Regular	Breath	Regular	Breath
FC-3	697 (162)	1301 (201)	858 (414)	1228 (285)	782 (328)	1265 (244)
FC-2r	-	1365 (110)	564 (85)	-	564 (85)	1365 (110)
FC-2l	624 (142)	-	-	1298 (104)	624 (142)	1298 (104)
FC-4r	1044 (212)	1365 (118)	732 (220)	-	836 (260)	1365 (118)
FC-4l	726 (208)	-	877 (170)	1412 (212)	776 (206)	1412 (212)

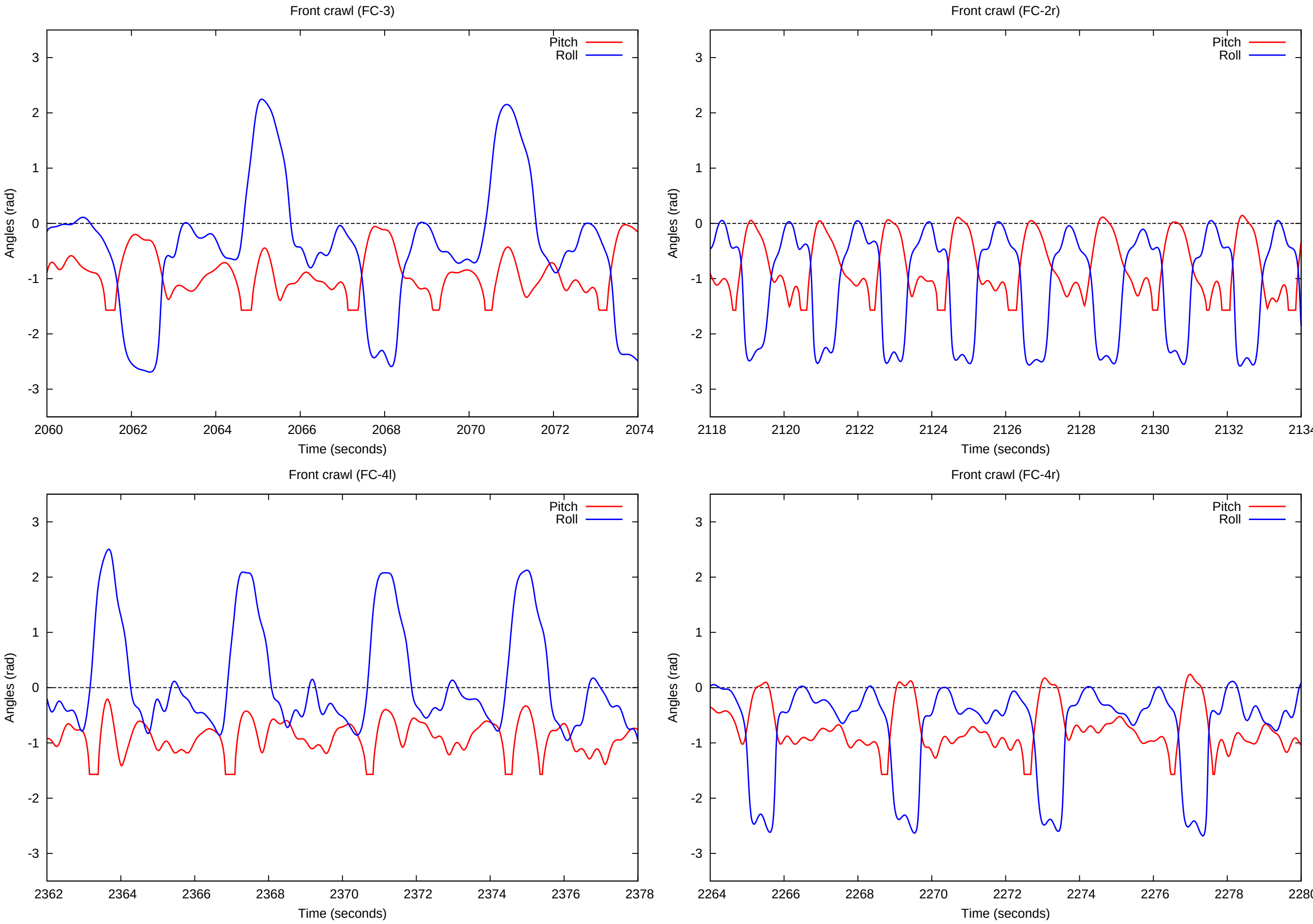

Fig. 6. Pitch and roll angles as measured during front crawl. Each swimming stroke is represented by a roll angle extrema. The main extrema are characteristic of the breathing roll motion. Top-left: breathing performed every 3 strokes (FC-3). The dominant roll angle extrema can be seen alternating between positive and negative values: the swimmer is breathing alternatively to the left and to the right side (bilateral). A higher pitch angle during right-side breathing might be sign of bad technique or that the left side is usually preferred. Top-right: breathing to the right every 2 strokes (FC-2r). The dominant roll angle extrema are always negative: the swimmer is always breathing to the right (unilateral). Bottom-left: breathing every 4 strokes to the left (FC-4l). Bottom-right: breathing every 4 strokes to the right (FC-4r).

3) Stroke symmetry: Most swimmers exhibit an asymmetric arm motion as demonstrated by Seifert *et al.* [4] using a measure of arm coordination based on the lag time between the beginning of propulsion in one arm and end of the propulsion from the other. It has been shown that the breathing actions increase this asymmetry in non-elite swimmers only. This phenomenon is obvious when looking at Figure 6: the breathing patterns to the left and right are significantly different for this subject. The swimmer seems to be taking a break in the roll motion when breathing to the right whereas the roll angle is much smoother when breathing to the left. Table III also provides information on stroke asymmetry. For example the breathing-to-regular stroke duration ratio is 2.4 for FC-2r, but only 2.1 for FC-2l. Similarly, this ratio is 1.9 for the right-side strokes in FC-3, but 1.4 for the left-side ones. This means that for these three breathing patterns, the swimmer takes proportionally more time breathing to the right side. Interestingly, the opposite trend can be observed when breathing every four strokes (FC-4r and FC-4l). This might be due to significant changes in motion patterns due to the overall longer duration between breaths.

VI. Conclusion and Future Work

In this paper, we have proposed the use of a single miniaturised accelerometer-based sensor for swimming motion analysis. By deriving the pitch and roll angles, it is possible to detect the type of stroke and the wall push-offs. Lap count and split times can also be derived. Further motion features such as stroke timing are proposed. The system proposed represents a non-intrusive, practical deployment of wearable sensors for swim performance monitoring. For elite swimmers, the development of miniaturised sensors worn on wrists and ankles would provide further insights into the biomotion patterns for more detailed performance analysis. Finally, a video-based validation of the proposed system is also being considered.

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