# Freestyle Swimming Analysis of Symmetry and Velocities using a MEMS based IMU: Introducing a Symmetry Score

Andy Stamm[1,2,a] and Igor Shlyonsky[3]

[1]Faculty of Technology and Bionics, Rhine-Waal University of Applied Sciences, 47533 Cleve, Germany

[2]Griffith School of Engineering, Griffith University, 4111 Nathan, QLD, Australia

[3]MySwimEdge, CA, U.S.A.

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Abstract: MEMS sensors (IMU's) are widely available nowadays and tend to be used more often in sports monitoring. Especially in swimming these sensors have seen rapid development in the past years. These sensors have very good measurement capabilities today, but the automatic analysis of the gathered data has not yet been implemented. Our objective is to develop and validate an automatic analysis which can provide the swimmers/coaches with nearly immediate feedback on a smartphone/tablet. Ten swimmers ranging from novice to elite have been participating in this study performing freestyle in either 25m or 50m pools. All trials were recorded with a 3-axis accelerometer. The symmetry parameters have been extracted from the recorded data after these were high-pass filtered to remove the gravity from the signal and a zero crossing detection algorithm was applied. The results showed a very strong relation to results obtained by other researchers.

## 1 INTRODUCTION

Since many years, the performance of athletes in swimming was evaluated by coaches sometimes under the help of bulky and complex equipment such as (multi) video camera systems and/or tethered velocity meters (Craig & Pendergast, 1979; Craig, Termin, & Pendergast, 2006; Stamm, Thiel, Burkett, & James, 2009). Operating such equipment usually needs a special trained person and additionally one expert for the data analysis, thus not allowing using this equipment on a regular basis. Furthermore a tethered device allows only investigating the movement into one direction; namely only one swimming lap at a time. This leads to athletes/coaches not using this equipment very often.

Nowadays athletes have become too competitive and sometimes a tenth of a second can decide upon gaining the next better place (Dadashi, Millet, & Aminian, 2013; Magalhaes, Vannozzi, Gatta, & Fantozzi, 2015) thus pushing the needs to monitor basically each training session or competition.

Inertial Measurement Units (IMU's) have become smaller in size and lighter in weight in recent years, allowing using such devices without any disturbance and performance problems. These devices are nowadays waterproof, easy to use (can be placed by the athlete) and are able to record multiple training sessions (Callaway, 2015; Guignard, Rouard, Chollet, & Seifert, 2017; Stamm & Thiel, 2015). IMU's can nowadays be used to find key factors such as stroke rate, split times, mean velocity, and arm symmetry. The last one has only been presented by (Stamm & Thiel, 2015) and is still novel in swimming research purely based on IMU's.

This research used a sacrum mounted MetaMotionC IMU (mbientlab, 2020) packaged in a waterproof casing to find the 3-axis acceleration dynamics of the swimmer. These data were used for automatic processing to find symmetry variables for further investigations and analysis. The objective of this research was to develop and validate an automatic analysis with the introduction of symmetry scores for immediate feedback to the athlete on a smartphone/tablet.

[a] https://orcid.org/0000-0002-9331-7431



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# 2 METHODS

## 2.1 Instrumentation

This study used a MetaMotionC 9-axis IMU with 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, barometer, and light sensor. It comes with built in Bluetooth for real time streaming and communication, internal memory for data storage, a CR2032 battery which last up to 48 hours of recording, a weight of less than 7g, and physical dimensions of 25 mm x 25 mm x 4 mm (width, height, depth) in a standard casing.

Figure 1 shows the sensor placed at the swimmer. The IMU was set at 100 Hz sampling rate.

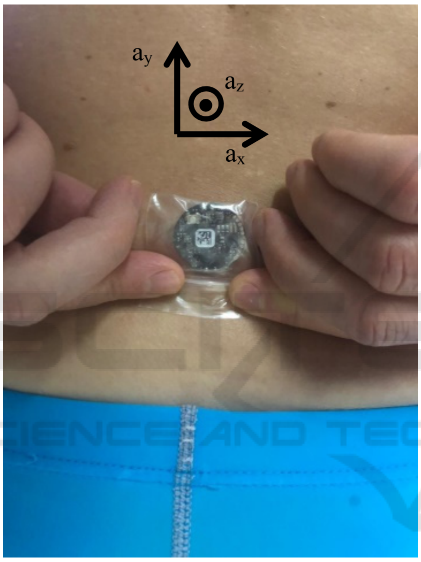


Figure 1: Sensor position and orientation at the swimmer.

## 2.2 Data Collection

Ten swimmers (9 males, 1 female, 37.5±12.4 years, 179.4±6.5 cm, 76.4±11.7 kg, see Table 1) with different levels of experience took part in this study. The experiments have been carried out in line with the Helsinki protocol for human research.

Data were collected at a 25m temperature controlled indoor pool. The swimmers where asked to perform an individual warm-up procedure to reduce the risk of injuries before they swam four laps which were recorded at different efforts. We expected a large variability as the efforts have been self-determined by the swimmers (low, medium, and full).

In this study, the IMU was taped firmly to the lower back of the swimmer to reduce unwanted IMU movements and to minimize skin movements. The forward direction is represented by the $a_y$, the mediolateral direction by $a_x$, and the anterior-posterior direction by $a_z$.

Table 1: List of swimmers with their height, mass, age and experience.

| Swimmer | Height (cm) | Mass (kg) | Age (years) | Experience | Gender |
|---|---|---|---|---|---|
| 1 | 183 | 79 | 29 | international | male |
| 2 | 168 | 53 | 49 | amateur | female |
| 3 | 172 | 82 | 37 | amateur | male |
| 4 | 182 | 82 | 48 | intermediate | male |
| 5 | 192 | 82 | 23 | amateur | male |
| 6 | 178 | 81 | 52 | amateur | male |
| 7 | 183 | 79 | 29 | international | male |
| 8 | 183 | 85 | 26 | national | male |
| 9 | 175 | 80 | 44 | amateur | male |
| 10 | 180 | 90 | 51 | amateur | male |

The data were downloaded via Bluetooth at the end of each training session using the App “MetaBase” provided by Mbientlab on an Android device. The downloaded data were then further send via email to the analysis team.

## 2.3 Data Processing

Data processing was automatically undertaken using multiple Python scripts which were programmed to find important parameters to athletes and coaches.

The acceleration data recorded by the IMU and sent via email to the analysis team was firstly converted to gravitational units before it was high-pass filtered with a cut-off frequency of 0.3 Hz to seperate the sensor orientation from the wanted acceleration signal (James & Wixted, 2011; Stamm, James, & Thiel, 2012; Stamm & Thiel, 2015; Stamm, Thiel, Burkett, & James, 2011). This filter was applied to remove the gravity signal form the acceleration signal. A zero crossing algorithm was further applied to the data to automatically separate the left and right arm strokes.

Figure 2 shows the recorded acceleration signal for one swimmer (blue) with the present sensor orientation component (red) which was removed from the recorded signal before it was further processed. The zero crossing algorithm was then applied to the gravity corrected mediolateral acceleration data (body-roll) to find the individual left and right arm strokes (see Figure 3).

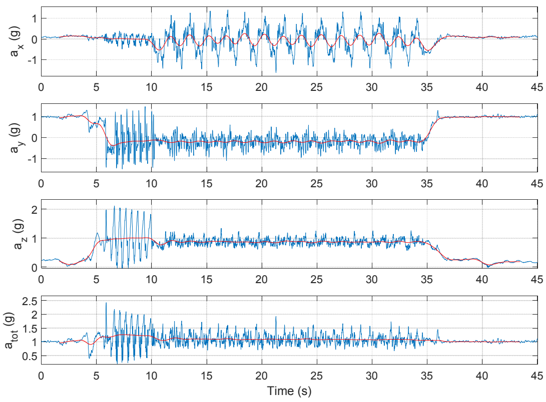


Figure 2: Raw acceleration (blue) with the overlapping gravity component (red).

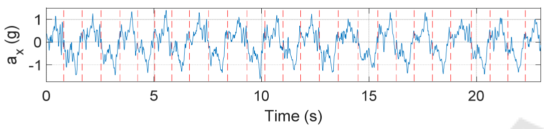


Figure 3: Gravity corrected body-roll acceleration signal (blue) with the overlapping zero-crossing detection result (red).

A lap velocity and lap distance profile were calculated as described by (Stamm et al., 2012) to investigate the symmetry of the swimmer in terms of timing, max/min arm velocity, distance, stroke rate, and stroke length.

Figure 4 presents a typical lap velocity profile for a 25m freestyle swimming lap with the push-off phase, swimming phase, and the stop phase. The focus for the automatic symmetry detection was hereby set on the swimming phase. The algorithm was set to detect the second stroke at the start, as sometimes the first stroke coincides with the push-off phase which leads to a slightly disturbed acceleration signal, and to stop at the second last stroke, as the last stroke quite often coincides with the stop of the lap.

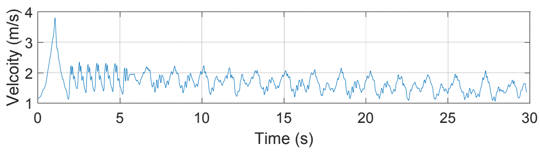


Figure 4: Lap velocity profile of a 25m freestyle swimming lap.

Figure 5 shows a typical left and right arm intra-stroke velocity profile extracted from a 50m freestyle swimming phase whereby Figure 6 presents the left and right arm distance extracted from the lap distance profile after the zero-crossing detection algorithm was applied.

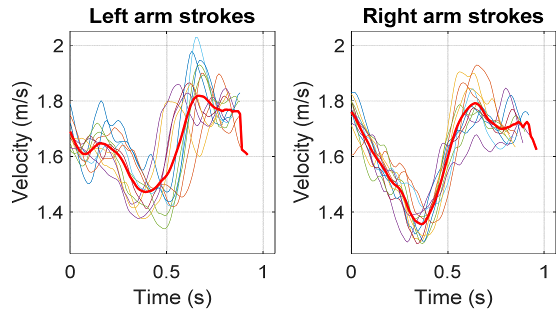


Figure 5: Left (a) and right (b) arm intra-stroke velocities of the swimming phase of a 25m freestyle swimming lap.

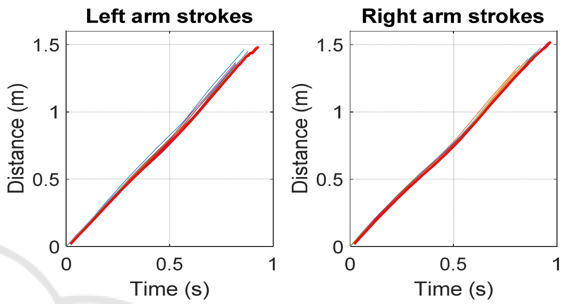


Figure 6: Left (a) and right (b) arm distances of the swimming phase of a 50m freestyle swimming lap.

The investigated symmetries are now translated into a simple symmetry score for the three individual investigated parameters (stroke duration, length, velocity) so that the swimmer can directly interpret the score to help improving the swimming style (see equation 1-3).

It needs to be mentioned that the symmetry scores have been calculated using average left and right arm timings, lengths, and velocities.

$$t_{symmerty\_score} = 1 - (t_{left\_arm} - t_{right\_arm}) \tag{1}$$

Equation 1 describes the symmetry score for the stroke duration considering the difference between the left and right arm stroke. An ideal symmetry would therefore always provide the result t=1, while t<1 would present longer left arm stroke duration, and t>1 would present a longer right arm stroke duration.

$$l_{symmerty\_score} = 1 - (l_{left\_arm} - l_{right\_arm}) \tag{2}$$

Equation 2 describes the symmetry score for the length of the stroke considering the difference between the left and right arm stroke. An ideal symmetry would be described by l=1, while l<1 would describe a longer left arm distance and l>1 would describe a longer right arm distance.

$$v_{symmerty\_score} = 1 - (v_{left\_arm} - v_{right\_arm}) \tag{3}$$

Table 2: Left and right arm mean stroke durations, stroke lengths, and average velocities including the standard deviation (SD) for the first lap of each swimmer.

| Swimmer | LEFT Arm Stroke Duration (s) ± SD | Right Arm Stroke Duration (s) ± SD | Left Arm Length (m) ± SD | Right Arm Length (m) ± SD | Left Arm Velocity (m/s) ± SD | Right Arm Velocity (m/s) ± SD |
|---|---|---|---|---|---|---|
| 1 | 1.21 ± 0.11 | 0.98 ± 0.03 | 2.41 ± 0.31 | 1.85 ± 0.09 | 1.96 ± 0.18 | 1.89 ± 0.24 |
| 2 | 1.07 ± 0.13 | 1.12 ± 0.10 | 0.83 ± 0.10 | 0.88 ± 0.08 | 0.79 ± 0.07 | 0.79 ± 0.11 |
| 3 | 0.82 ± 0.07 | 0.83 ± 0.07 | 0.83 ± 0.07 | 0.89 ± 0.11 | 1.02 ± 0.13 | 1.06 ± 0.19 |
| 4 | 0.95 ± 0.10 | 0.99 ± 0.06 | 1.19 ± 0.12 | 1.28 ± 0.07 | 1.26 ± 0.19 | 1.29 ± 0.20 |
| 5 | 1.01 ± 0.09 | 0.86 ± 0.05 | 1.08 ± 0.11 | 0.92 ± 0.07 | 1.07 ± 0.10 | 1.06 ± 0.12 |
| 6 | 0.84 ± 0.04 | 0.96 ± 0.06 | 0.94 ± 0.05 | 1.08 ± 0.06 | 1.13 ± 0.24 | 1.12 ± 0.23 |
| 7 | 1.32 ± 0.18 | 1.51 ± 0.29 | 1.21 ± 0.21 | 1.31 ± 0.21 | 0.91 ± 0.15 | 0.87 ± 0.18 |
| 8 | 1.11 ± 0.07 | 1.07 ± 0.04 | 1.39 ± 0.10 | 1.23 ± 0.04 | 1.26 ± 0.14 | 1.17 ± 0.11 |
| 9 | 0.90 ± 0.09 | 0.93 ± 0.09 | 0.80 ± 0.08 | 0.80 ± 0.08 | 0.88 ± 0.12 | 0.87 ± 0.10 |
| 10 | 1.38 ± 0.06 | 1.36 ± 0.04 | 1.21 ± 0.07 | 1.14 ± 0.06 | 0.88 ± 0.13 | 0.83 ± 0.11 |

Equation 3 describes the symmetry score for the average stroke velocity considering the difference between the left and the right arm. An ideal symmetry would be described by $v=1$, while $v<1$ would describe a faster left arm velocity and $v>1$ would describe a faster right arm velocity.

It should be noted that larger deviations come from the fact that the symmetry scores were not normalised.

All automatic calculations have been validated against manual data analysis undertaken in MATLAB as described by (Stamm et al., 2012). There has been no significant difference between the automatic and manual data analysis found.

## 3 RESULTS

A total of 30 freestyle swimming laps have been analyzed for the participants (see Table 1).

The zero-crossing detection algorithm applied to the acceleration, lap velocity, and lap distance profile data allowed the separation of left- and right arm strokes, thus allowed the symmetry investigation of the involved swimmers with the results of the first swim of each swimmer being presented in Table 2.

The symmetry scores were calculated according to equations 1-3 which have been described in the previous chapter and are presented in Table 3. It can be seen that the symmetry scores for swimmers who had a large difference between the left and right arm duration/length/velocity are significantly below or above the ideal score of 1.

Table 3: Symmetry scores for the first lap of each swimmer calculated under usage of mean stroke time, length, and velocity

| Swimmer | Time symmetry score | Length symmetry score | Velocity symmetry score |
|---|---|---|---|
| 1 | 0.77 | 0.44 | 0.93 |
| 2 | 1.05 | 1.05 | 1.00 |
| 3 | 1.02 | 1.06 | 1.05 |
| 4 | 1.04 | 1.09 | 1.04 |
| 5 | 0.85 | 0.84 | 1.00 |
| 6 | 1.12 | 1.14 | 1.00 |
| 7 | 1.19 | 1.10 | 0.97 |
| 8 | 0.96 | 0.84 | 0.91 |
| 9 | 1.02 | 1.00 | 0.99 |
| 10 | 0.98 | 0.93 | 0.96 |

Whereby a score smaller 1 for the stroke duration means that the left arm took longer, a score smaller 1 for the length means that the left arm traveled a longer distance, and a score smaller 1 for the average velocity meant that the left arm had reached a larger velocity.

For the purpose of swimming methodology more attention should be given to the situations where all three scores are either smaller or larger than 1.

## 4 CONCLUSIONS

The arm symmetry of ten swimmers performing freestyle swimming laps with different levels of experience has been investigated using a MEMS based IMU. The recorded tri-axial acceleration signal was firstly high-pass filtered to remove the unwanted gravity component of the acceleration signal. The gravity corrected acceleration signal was then used to calculate the lap velocity profile using an approximation to the numerical integration as well as the lap distance profile (Stamm et al., 2012). A zero-crossing detection algorithm was then applied to separate the left from the right arm strokes to facilitate the arm symmetry investigations. The results found average left and right arm velocities in the range from 0.53 m/s up to 2.08 m/s which goes in line with (Craig & Pendergast, 1979; Craig et al., 2006; Stamm et al., 2011).

It was further proposed to introduce three simple numbers to provide (amateur) swimmers with an index to show them potential improvements in their applied swimming style. The three symmetry scores have been based on the automatic analysis of freestyle swimming laps and the parameters: stroke timings; stroke length; and average stroke velocity. The simplicity of the proposed symmetry scores reflects in a simple way of interpretation as a perfect symmetry would be reflected by the score 1. A smaller score meant that the left arm took longer in terms of arm timing; that the left arm had a longer distance, and that the left arm had reached a higher velocity, respectively. A score larger 1 reflects the symmetry shift towards the right arm.

Considering the simplicity of the proposed symmetry scores, it can be understood by every swimmer and directly translated to a change in the swimming style to further improve the technique.

First feedback was sought by the authors from swimmers participated in that study and proofed that this simple symmetry numbers were widely accepted by the participants as an easy and understandable symmetry score.

It is evident that the proposed methods present simple symmetry scores and that they can be used to help swimmers improving their swimming style. It can be concluded that this simple method can be used to substitute more complex equipment and therefore help the swimmer to easily improve their swimming symmetry.

The next step would be to involve coaches to be able to have their feedback to further improve the methods applied and optimise the form of presentation. This could be i.e. to provide the swimmers with a simple to use app to which the IMU can be connected to start/stop the recording; upload the data for an automatic analysis; and a graphical presentation of the results, and individual stroke analysis. All of this should be made available to the swimmer within minutes to be able to change the swimming style while still performing the training session.

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## REFERENCES

Callaway, A. J. (2015). Measuring Kinematic Variables in Front Crawl Swimming Using Accelerometers: A Validation Study. *Sensors, 15*(5). doi:10.3390/s150511363

Craig, A. B. J., & Pendergast, D. R. (1979). Relationships of stroke rate, distance per stroke, and velocity in competitive swimming. *Medicine & Science in Sports & Exercise, 11*(3), 278-283. Retrieved from http://journals.lww.com/acsm-msse/Fulltext/1979/01130/Relationships_of_stroke_rate,_distance_per_stroke,.11.aspx

Craig, A. B. J., Termin, B., & Pendergast, D. R. (2006). Simultaneous recordings of velocity and video during swimming. *Portugese Journal of Sport Sciences, 6*, 32-36.

Dadashi, F., Millet, G., & Aminian, K. (2013). Inertial measurement unit and biomechanical analysis of swimming: an update. *61*, 21-26. Retrieved from http://infoscience.epfl.ch/record/189819/files/Sportmedizin%20-%20Dadashi%20et%20al-%202013.pdf

Guignard, B., Rouard, A., Chollet, D., & Seifert, L. (2017). Behavioral Dynamics in Swimming: The Appropriate Use of Inertial Measurement Units. *Frontiers in Psychology, 8*, 383. Retrieved from https://www.frontiersin.org/articles/10.3389/fpsyg.2017.00383

James, D. A., & Wixted, A. (2011). ADAT: A Matlab toolbox for handling time series athlete performance data. *Procedia Engineering, 13*, 451-456. doi:10.1016/j.proeng.2011.05.113

Magalhaes, F. A. d., Vannozzi, G., Gatta, G., & Fantozzi, S. (2015). Wearable inertial sensors in swimming motion analysis: a systematic review. *Journal of Sports Sciences, 33*(7), 732-745. doi:10.1080/02640414.2014.962574

mbientlab. (2020). MetaMotionC (MMC). Retrieved from https://mbientlab.com/metamotionc/

Stamm, A., James, D., & Thiel, D. (2012). Velocity profiling using inertial sensors for freestyle swimming. *Sports Engineering*, 1-11. doi:10.1007/s12283-012-0107-6

Stamm, A., Thiel, D., Burkett, B. J., & James, D. A. (2009). Roadmapping performance enhancement measures and technology in swimming. *The Impact of Technology in Sport II*, 213-217. Retrieved from

http://research.usc.edu.au/vital/access/manager/Repository/usc:6000
Stamm, A., & Thiel, D. V. (2015). Investigating Forward Velocity and Symmetry in Freestyle Swimming Using Inertial Sensors. *Procedia Engineering, 112*, 522-527. doi:http://dx.doi.org/10.1016/j.proeng.2015.07.236
Stamm, A., Thiel, D. V., Burkett, B., & James, D. A. (2011). Towards determining absolute velocity of freestyle swimming using 3-axis accelerometers. *Procedia Engineering, 13*, 120-125. doi:10.1016/j.proeng.2011.05.061