

## CrawlStroke on a watch

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### Abstract

The CrawlStroke app<sup>1</sup> uses a watch for recording crawl data and a phone for presenting it. The author relied on practical front-crawl knowledge, some instructions on the web, the pre-installed API of the watch and the phone and the sensor data of the watch. Therefore the report follows a how-I-did-it style.

Key features of the CrawlStroke app:

- it is implemented on unobtrusive multipurpose devices: watch and phone
- it addresses recreational swimmers
- it uses a simple 2-phase model of strokes
- it focuses on the swimmer's shoulder joint for stroke detection
- it derives stroke boundary events from short sensor data histories
- it exploits synchronization of arm moves

After the description of the app, the report inspects related approaches. The key interests are set by the own development experience:

- defining an empirical model of front crawl
- tracking crawl performance on inertial measurement devices (IMUs)
- the user experience

**Keywords:** front crawl; freestyle; stroke; swimming style; inertial measurement unit; IMU; sensor; smartwatch; smartphone; user interface; user experience (UX)

## 1. CrawlStroke

### A simple two-phases model of front crawl stroke

#### Pull and recover

Freestyle or front crawl is a popular swimming style. It is said to be the fastest one. Almost everybody recognizes it easily:

Both arms of the swimmer go back and forth along the body in a windmill-like movement. They alternate. When the left arm goes back through the water and pulls, the right arm returns forward through the air, and vice versa. The legs paddle steadily.

Fig. 1 shows the two phases of freestyle swimming:

- pulling when the arm is drawing through the water
- recovery when the arm returns forward through the air

Most of the swimmer's speed is due to the arms.

The paddling legs contribute less, but they stabilize the body in the water.

While the arms are moving in a circle all time, the swimmer advances. The arms repeat moving in the two phases from above:

- pulling: dipping into the water and drawing backward until they reach a return point of the shoulder
- recovery: moving from the shoulder rotation back forward by the air until the front dip-in position is reached

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<sup>1</sup> <https://appadvice.com/app/crawlstroke-swim-better/1390335321>

Two events separate pulling and recovery:

- the shoulder turn event
- the dip-in event

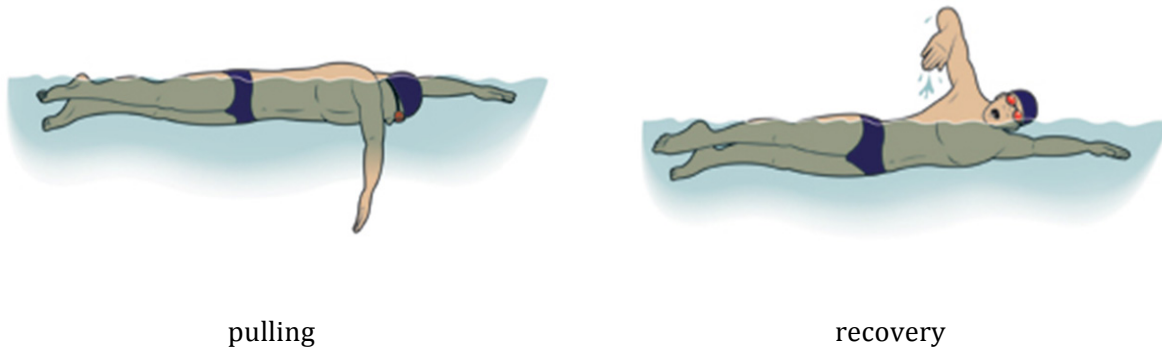


Figure 1. Freestyle swimming as seen in Experience Life (<https://experiencelife.com/>)

The moves need time intervals for making their way while the events occur at a point of time. Together the four items constitute a stroke. Strokes again take time, and one stroke follows the other until the swimmer stops them.

The following drawing (fig. 2) illustrates a freestyle stroke conforming to this view.

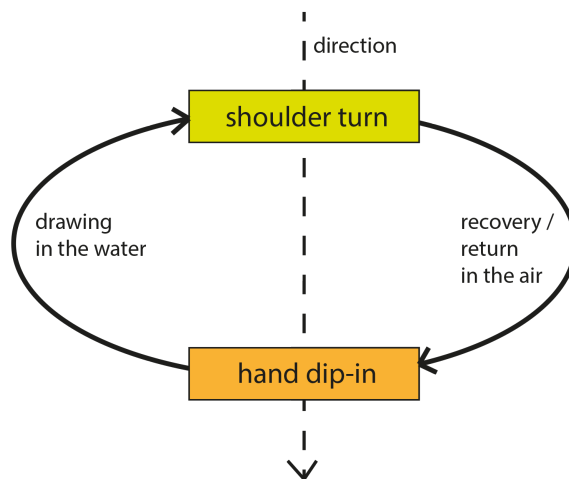


Figure 2: Front crawl stroke with drawing and recovery moves, separated by shoulder turn and dip-in events

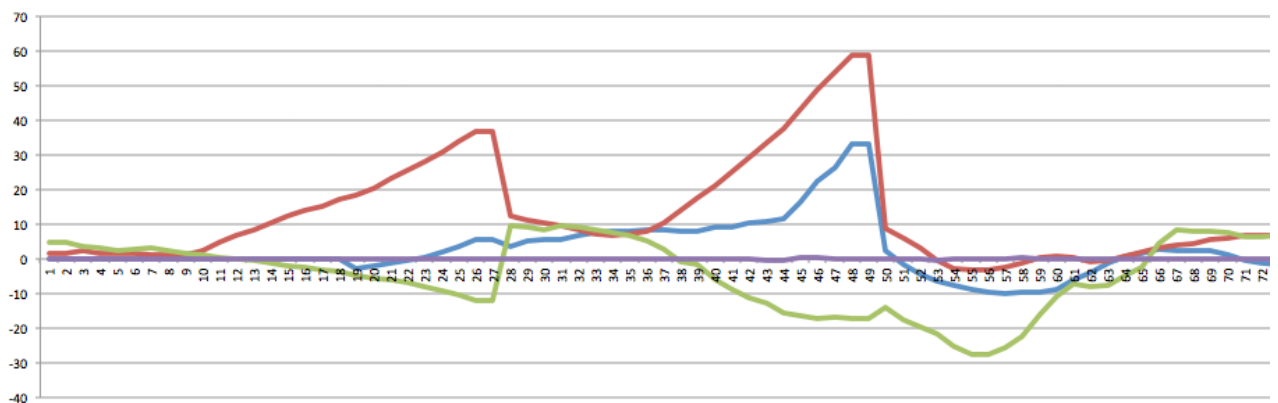


Figure 3. Attitude values of a freestyle / front crawl sample: red-brown is roll, green is pitch, blue is yaw

Fig. 3 shows a part of a crawl sample as seen by watch sensors. It displays time on the x-axis and degrees on the y-axis.

- The red-brown *roll* line presents two sharp drops. They depict stroke boundaries - the rotation of the shoulder joint when the swimmer returns the arm forward for recovery.
- The *yaw* value (in blue) is often accompanying the roll movement. In general it depicts the distance of the watch from the swimmer's trunk.
- The green *pitch* value crosses the zero level line - up and down. A zero pitch value corresponds to a horizontal position. The water surface is horizontal. Values above the horizontal line tell that the hand is in the air (recovering), with values below it is under water (drawing/pulling phase).

The shoulder joint roll jump is a key event of stroke detection. It starts and ends strokes. The pass of the pitch zero line corresponds to the dip-in of the hand. This event marks the boundary between a recovery and a pull phase of a stroke.

Tracking both events requires following their history:

- The shoulder roll jump event is derived from a stack of two roll values in sequence. Their minimum jump is currently set to 30°.
- The hand dip-in is discovered from a 4 items pitch history. Three values must stay on the current side of the zero line, followed by one transcending it.

### **Synchronized arm moves**

Data input tells what the watch-bearing wrist does. Front crawl swimming is synchronized: while one arm is pulling, the other recovers. At the end they must meet for the changeover. The values of the watch-bearing arm allows to estimate values of the second arm:

- While the arm with the watch is recovering, it passes through the air and cannot pull. Acceleration values arriving during this time are assigned to the other arm although some own motion of the watch-bearing wrist may mix in.
- Left and right arm take turns. As they meet at the end of a move, the shoulder roll event of one arm is synchronized with the dip-in of the other arm. Thus the phase duration of the arm without watch can be set.
- The watch can be set to the right and the left wrist for counterchecks.

## **On the watch**

### **The attitude reference frame**

Besides the limits of the position on the swimmer's wrist the perception of the watch is set by its sensor capabilities. It cannot pick up what is beyond its grasp.

At a given time rate the timer retrieves a sensor shot (example in fig. 5). The shot brings the acceleration and the attitude frame values. Acceleration is a single-track property. For swimming its forward acceleration - speedup - is considered. The attitude reference frame points into three directions: forward or backward, to both sides, and up and down.

The attitude reference frame controls the position of the watch in space. The watch is like a flying object. The fruitfly (*Drosophila*, see fig. 4 and <http://flybase.org>) below displays the three main axes of the watch (and phone) attitude reference frame. It can change its position by turning around its:

- longitudinal axis (value *roll*)
- lateral axis so that it is lifting or dropping its head or tail (value *pitch*)
- perpendicular axis when directing the nose laterally to the right or the left side (value *yaw*).

All these movements may combine.

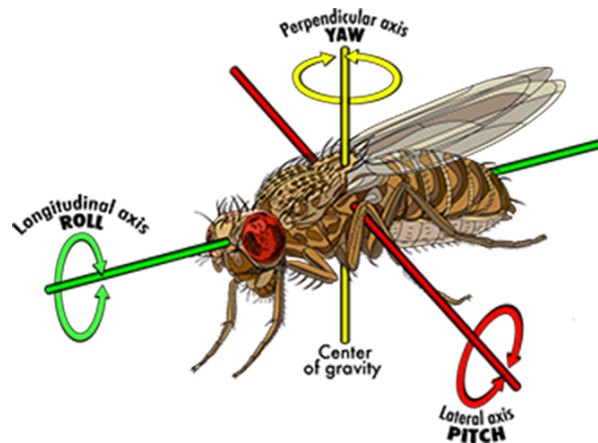


Figure 4: The reference frame with axes for pitch, roll, and yaw, demonstrated by the fruitfly

The attitude reference frame is set at start. As the fruitfly it looks forward: on the watch the default reference frame points to the fingertips. The watch runs counterclockwise. It uses the 360° of the circle, with a positive part 0° -- 180° and a negative half -180° -- -0°.

	Left hand		Right hand	
pitch	↑ up	↓ down	↓ up	↑ down
roll	↓ to right	↑ to left	↓ to right	↑ to left
yaw	↓ to right	↑ to left	↓ to right	↑ to left

Table 1. Attitude values with ups and downs (arrows) and interpretation, yellow background marks items needed for event detection

Depending on the location of the watch on the left or right wrist the sensor values must be interpreted differently:

- Envisage the dipping of the hand so that *pitch* will cross the zero value. On the left hand, the range will sink from positive values to a negative one. On the right hand, the dip-in sequence begins with negative values and rises to a positive one.
- Consider the *roll* move. Counterclockwise it drops when the wrist turns to the right, it rises when the wrist turns to the left. On the right arm, the shoulder rolls to the left and will deliver a positive jump. On the left arm, the shoulder rolls towards the trunk - to the right - and produces a drop of the value.
- For *yaw* values, arms reaching out from the bodyline are expected to deliver falling values on the right wrist, and increasing ones on the left.

Table 1 puts these deliberations together. The items required for event detection are highlighted in yellow.

## Sample and stroke processing overview

A swimming sample is a sequence of strokes. It starts with a first stroke and ends with the last one.

- The normal case is an intermediary stroke. It starts when its predecessor ends. At its end, the next stroke starts up.
- For the first stroke of a sample the entry point must be found from possibly unregulated incoming sensor data.
- The last stroke of a sample ends with no follower, but with more sensor data running in until the user stops it.

The first stroke of a sample starts when the first shoulder roll event is discovered. The last stroke ends with the last shoulder roll that could be verified.

Stroke processing includes the following tasks:

- As shots arrive, their time, the attitude and acceleration values are inspected. Pitch, roll, and yaw are stored if they are the current maxima or minima of the stroke.
- For every shot the time of the forerunner is put aside.
- Each shot dataset is examined on whether it brings a shoulder roll or a hand-dip event. The event state is set accordingly, so that the current phase (pull or recovery) is known.
- Acceleration values are assigned to the active watch-bearing arm when they arrive during a pull phase. During recovery, they are attributed to the other arm. In both cases, the current maxima are stored.
- The duration of a recovery is the interval between the shoulder roll time and the hand dip-in time.
- The pull phase lasts from the hand dip-in time to the shoulder roll time.
- The watch-bearing arm's recovery time is the other arm's pull time, and vice versa.
- The duration of the stroke is found by adding pull and recovery times.
- At hand dip-in event and at shoulder roll event the speed between the next-to-last and the last shot is stored away. The values are used for estimating the body speed.
- At the shoulder roll event, a stroke finishes. Its data is packed away before the next stroke is set on.

When the swimmer starts recording, the timer pauses for 3 seconds so that the swimmer can change from watch handling to swimming. After that, sensor shots are retrieved at a 1/10 second rate. The sample ends with the user's stop. All its strokes are put into the sample array. The swimmer can send the sample array to the phone and start the next sample. Up to three samples are stored on the watch. They can be sent to the phone at a single blow.

### Some data code

```
shotcount: 33 time: 18-11-08 08:38:49.312  
  
pitch: -30.440363007323842  
yaw: -45.657676752259256  
roll: -50.2129685109857  
speedup: -0.14506604882532645
```

*Figure 5. A sensor shot*

Fig. 5 presents an example shot. A sensor shot brings its time, the attitude value degrees and the speedup in m/sec<sup>2</sup>. The degrees are derived from incoming radians values.

From the shots attitude and speedup values are picked up and aggregated. Besides standard processing, all shots are inspected on whether they indicate an event.

```

shotcount: 46 time: 18-11-08 08:38:51.728
pitch: -27.991037033308146
yaw: -68.75002455377428
roll: -80.53922744256835
speedup: 0.1765267129680059

```

```

shotcount: 47 time: 18-11-08 08:38:51.745
pitch: -6.695427879405609
yaw: -24.467630039161843
roll: 7.65473657653977
speedup: -0.2906598115772548

```

```

TRYING PEAKTEST
peakFound: true

```

*Figure 6. Two sensor shots displaying a roll difference of > 88° - a shoulder turn.*

For a shoulder roll event, the roll value must jump 30 degrees or more in two subsequent shots. Fig. 6 shows a roll jump situation. Between two shots, the roll value switches from a peak of -80 to a low of +7, creating a difference of some 88°. Returning to table 1 one may conclude that the watch observes the right arm of the swimmer.

The dip-in event of the hand corresponds to a pitch passing the zero line. There must be a first negative pitch value after a history of positive ones, or vice versa. Forerunners are shifted through a stack of 3 positions. If after three positive values a first negative one is coming in, or vice versa, a dip-in event is assumed. The new value is put into the stack. Fig. 7 presents an example.

```

shotcount: 362 time: 18-11-12 07:06:31.406
pitch: 11.707451290074927
yaw: -146.57285952783695
roll: -61.03592357740656
myspeedup: -0.3136050462877306

```

```

TRYING DIPTTEST
right hand dip - pitch up to > 0
currentdips: [11.707451290074927, -10.76861258755271, -
11.464378788592006]
dipFound: true

```

*Figure 7. A dip-in event: last pitch value > 0, forerunners < 0*

In order to represent swimming samples, the observed strokes are stored with their properties in a sample container. Their keys adapt to the later user view on the phone:

- For characterizing the pull and recover/back moves, three types of features are entered: duration, maximum speedup, and the speed reached at their end.
- The maxima and minima of the recorded attitude values are packed in, too.

An example with the feature and value pairs of a stroke is displayed in fig. 8. A stroke enters into its sample container like this.

```

["backDuration": 1.0949400663375854, "pullendSpeed": -0.003515612508393403, "pitchMin": -
70.62008257216038, "rollMax": 75.98841408779496, "yawMin": -127.41011228714609, "backendSpeed": -
0.003521733966987812, "maxpullSpeedup": -0.36916376289915376, "strokeDuration": 3.427142024040222,
"rollMin": -100.66835059956486, "yawMax": 1.8242771251896819, "pitchMax": 33.70404047116582,
"maxbackSpeedup": 0.5677406552950721, "pullDuration": 2.3322019577026367]

```

*Figure 8. Example of stroke data*

What does not fit into a stroke is canceled. Up to three samples are saved on the watch. For inspection and permanent storage the user sends the samples to the phone.

## User interface

### On the watch

On the watch interface, users are welcomed with a summary of their current stroke. At the beginning it has no values. By a strong tap they switch to the menu for app handling. There they can start recording, stop it, switch back to the summary and send samples to the phone. The background color reveals the state of processing: black is basic, fuchsia is recording, blue is saving / sending to the phone. Fig. 9 presents the watch screens.

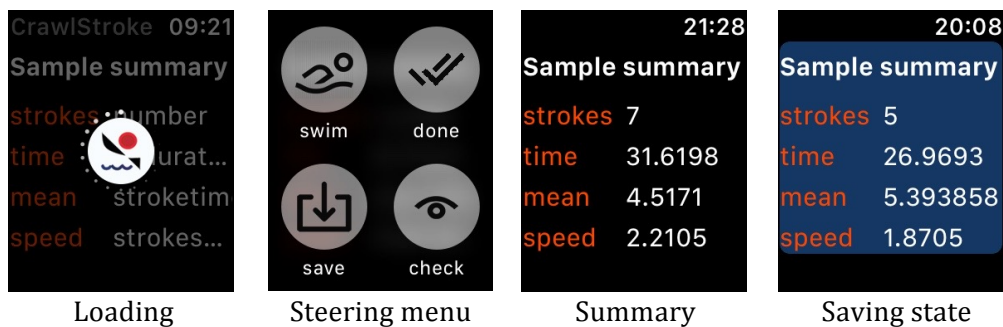


Figure 9. Screens of the CrawlStroke watch

### On the phone

Watch and phone specialize according to their possibilities: the watch sensors measure the values, the phone presents them.

The phone receives samples filled with stroke data as shown in fig. 9, up to 3 at a time. On the phone user interface the samples are distributed on tables so that users can make sense of them:

- an overview of all stored sample
- displays of individual strokes
- a sample summary

On fig. 10, all three types of phone displays are illustrated.

#### Overview table

At arrival, a sample package from the watch is tagged with its arrival time. To individualize samples, the arrival time is increased by one minute for every follow-up sample. Tapping on the table item itself leads to the strokes screen, tapping on the sum button passes to the sample summary. The red buttons at the top delete items: the right one starts deleting, the left one returns to the standard display. The info button at the top leads to the information screen illustrated in fig. 11.

#### Stroke table

On the stroke screen all strokes of a sample have a display of their own, listing their available properties as received from the watch. A strokesSpeed feature is added. It averages pullendSpeed and backendSpeed. From strokeSpeed and stroke duration, a strokeDistance value is approximated - the advance made during a stroke.

The table scrolls to the attitude max and min values at the bottom.



Figure 10. Data tables on the CrawlStroke phone

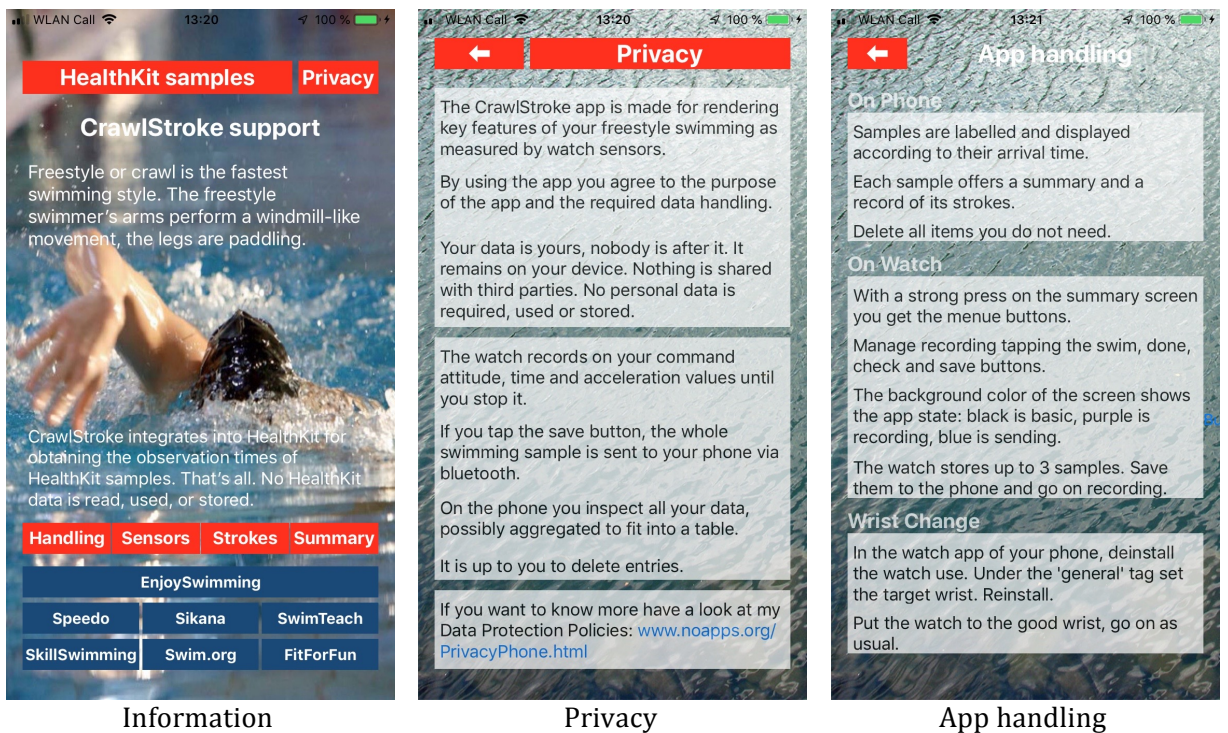


Figure 11. Information screen, Privacy declaration and App handling instruction



### *Sample summary*

The summary aggregates the figures of all strokes of the sample by averaging them, adding them up or setting ranges of minimum and maximum values. The sample distance results from adding up stroke distances.

### *Information environment*

The information environment on the CrawlStroke phone (see fig.11)

- establishes a connection to some of the many good freestyle advice offers on the web
- explains the CrawlStroke app's handling of user privacy
- instructs users on how to use the app, providing key information on its functions

## **2. Inspecting related work**

Developing the CrawlStroke app carved out some specific interests: what about

- the definition of the front crawl stroke
- the advance of IMU technology for investigating crawl performance of swimmers
- the user experience

in related and earlier approaches?

### **What front-crawl swimmers do**

Lenzi(2015)'s account on the history of swimming and swimming styles is great fun. People learned swimming as far as the techniques were shaped at their time. Today's basic front-crawl style was developed over many years and steps with intermediate stages. Much inspiration came from the Polynesia and Melanesia islands.

As swimming, investigating swimming performance has a history of development. It advances with its technical means. Sanders and colleagues (2017) illustrate how the measurement problem limited better knowledge on propulsion during front crawl swimming. Coaches and swimmers were victims of assumptions that later proved wrong.

An early definition of the front crawl stroke by Maglischo (1993, 2003), is reported and used by Ohgi and Yamamura (2000) and others, here abridged and slightly edited:

- *entry* and stretch: A swimmer enters his hand into the water and stretches his arm forward
- *downsweep*: The swimmer moves his hand downward. The extension of shoulder joint and the slight flexion of elbow joint of the swimmer cause this curvilinear downsweep motion.
- *catch*: The elbow rises up above the hand.
- *insweep*: The swimmer extends the shoulder and flexes the elbow joint with a body roll. The hand moves to midline of his body. The palm gradually rotates from out and back to in and up.
- *upsweep*: The further extension of the shoulder joint and elbow extension cause an upward hand motion. The swimmer extends his elbow joint. He must change his hand pitch angle properly in order to produce sufficient propulsive force.
- *release*: The swimmer's hand releases from the water.

Ohgi and Yamamura (2000) worked with two elite swimmers. They combined underwater cameras with an IMU device at the right wrist of the swimmers. In their study, Maglischo 's underwater moves of front crawl were confirmed by the acceleration values of the IMUs and the videotaping.

Chollet and colleagues (2000) used a four-phases front-crawl structure:

**Phase A:** entry. Entry and catch of the hand in the water, lasting from the hand's entry into the water to the beginning of its backwards movement.

- **Phase B:** pull. This phase corresponds to the time from the beginning of the hand backwards movement to the hand's arrival in the vertical plane to the shoulder. This phase is the beginning of propulsion.
- **Phase C:** push. This phase corresponds to the time from the hand's position below the shoulder to its release from the water.
- **Phase D:** recovery. This phase corresponds to the time from the hand's release from the water to its following entry into the water.

Here the front crawl stroke is defined by phases that are "actions between two times". Hand positions serve as boundary markers. Later researchers adopt this model, e.g., by McCabe and colleagues (2011), Callaway and colleagues (2015) and Hansen (2017).

Note that the shoulder joint roll is not mentioned as a possible boundary marker. In Psycharakis and Sanders (2010) and in Bächlin and colleagues (2009) the shoulder roll is defined as the roll of the upper trunk and part of the body roll.

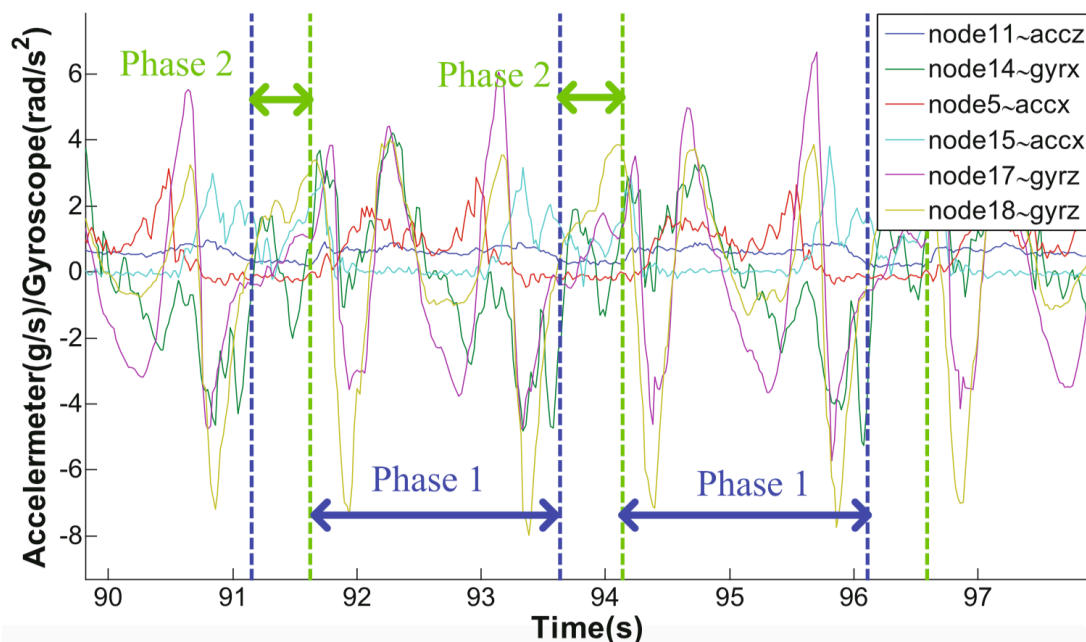


Fig. 12. Two phase segmentation of crawl stroke from Wang and colleagues 2016. Breathing phases are flagged in green, non-breathing phases in blue.

Wang and colleagues (2016) propose a two-phases organization of front crawl strokes. They distinguish breathing and non-breathing phases based on the movement of the trunk, picked up from sensors on the chest, the abdomen, left and right wrist, left and right shin. As fig. 12 shows, the sensor nodes contribute different values from their accelerometer or gyrometer input. The x values correspond to pitch changes, the z values indicate rolls around the longitudinal axis (compare to fig. 4 and to the much simpler watch sensor data of fig. 3).

The two-phase model that has advantages:

- it can be detected by IMU sensors
- it is simple enough for all front crawl swimmers, recreational swimmers included
- it may serve all swimming styles where breathing can be tracked

One may argue that breathing is not the only perspective for structuring front-crawls strokes. Focusing on the arm moves is more specific for front-crawl, while breathing covers all swimming styles. If the idea is to structure all styles by one feature, breathing serves best.

### Inertial measurement units (IMUs)

Inertial measurement units (IMUs) are electronic devices that record an object's position and movement using a combination of accelerometers and gyroscopes, often also magnetometers. IMUs may refer to GPS data. They can be implemented in many types of devices, e.g., devices for observing physical exercise such as swimming. IMUs may serve a specific function or a bigger range of applications. They measure the values at their specific location, so that every place of interest needs an IMU of its own.

Recent overviews by Guignard and colleagues (2017) and Mooney and colleagues (2016) report on IMU use for swimming. Both reports describe the "gold standard" of tracking swimmer performance: a two- or three-dimensional video camera equipment. Behind the cameras, sophisticated computing facilities are needed in order to reconstruct and integrate the data. The experimental setup of Callaway (2015) on fig. 13 gives an example of such a technical equipment. The huge computational effort is not shown, but it is there and it is essential.

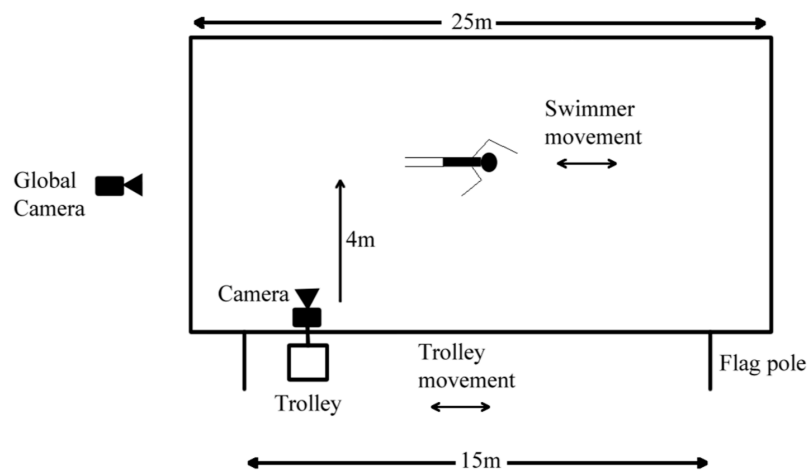


Figure 13. The experimental setup of Callaway (2015)

On one side the videos produce relevant results, on the other they impose limits because the heavy machinery restricts studies to laboratory environments with a few test subjects, a few strokes and considerable error rates. In spite of shortcomings, videotaping remains in use till now, often combined with IMU technologies.

Many researchers used upcoming IMUs for verifying swimming performance, with Ohgi and colleagues (2000) being first. They put the device on the swimmer's wrist. This was, however, not the favorite option of later researchers. Instead devices were distributed on the swimmer's body from the head to the calves and ankles. On their figure 4 (not reproduced here), Mooney and colleagues (2016) display 13 different locations, the sacrum and the wrist being the most frequented.

What can be detected from which body position is to be considered when placing the IMUs. According to Pansiot and colleagues (2010) on table 2, the arm location is fruitful for verifying front crawl features. The arm symmetry and antisymmetry can be exploited.

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	-	-	-	++

Table 2. IMU output from different body locations for front crawl (FC), backstroke (BaS), breaststroke (BrS), butterfly (Bf). Source: Pansiot and colleagues (2010)

Whereas early IMU adopters referred to acceleration values only, Davey and colleagues (2011) exploit gyrometer data, too. Other researchers also did. Angle values are exploited (Pansiot and colleagues (2010), see fig. 14, cf. the SwimMaster of Bächlin and colleagues (2009)).

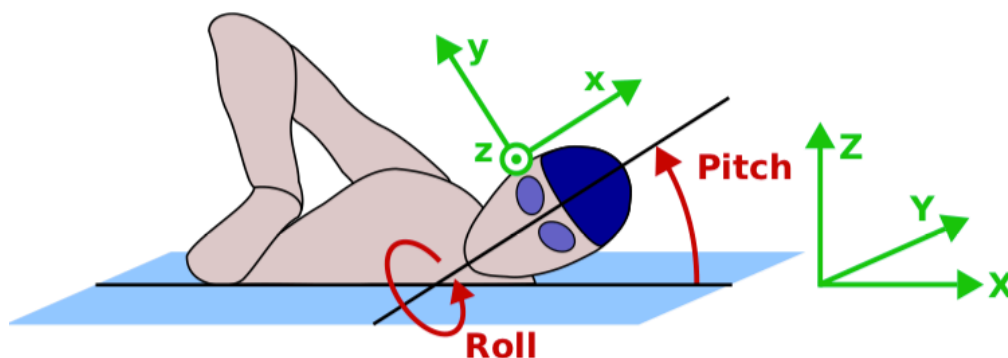


Figure 14. Angles seen during crawl observation with IMU on the head. Figure from Pansiot and colleagues (2010)

By now the complete reference frame of x - pitch, y - roll, and z - yaw values is in use, cf. Wang and colleagues (2016). As Mooney and colleagues (2016) observe, not all angles are treated equally: the shoulder joint angles are not explored so far.

Current standard features of assessment are stroke phase, stroke rates, stroke counts, and lap times. Other interests vary widely, for instance from dry-land swimming to the swimmer's current swimming style or skill level. Proving the validity of IMU analyses by comparing their results to video screening is still an issue in swimming and elsewhere, see e.g., Seifert and colleagues (2014) or Ganzevies and colleagues (2017).

## IMUs and users

IMUs sitting anywhere on the swimmer's body may be acceptable under test conditions. Researchers developed many ideas how to fasten them. IMUs are packed into swimsuit pockets, fixed with belts, attached to goggles, designed as wristbands or watch-style objects, and so on. A general problem is to keep them in place during swimming. Worse is that they may disturb the movement and falsify data.

Multiplying the IMUs has drawbacks of its own. Swimmers may not like too many of them. Processing must consider a range of individual devices. Evidently, a wristband IMU has hard times to get data about the swimmer's legs. Integrating all values with respect to their locations may engender huge processing efforts.

In the eyes of users, any devices that monitor their performance should be affordable, reliable and easy to use (Dadashi and colleagues 2013b). The authors observe that in 2013 stopwatches and elaborate video camera systems are in use for monitoring swimming. At that time, wearable self-monitoring devices are on the market, but waterproof solutions are still missing or just emerging.

For competitive swimmers and their trainers wearables may be dedicated to swimming, for casual swimmers they may cover more sports or other activities. Perego and colleagues (2015) pack the IMUs into pockets on the back of the swimsuit between the shoulder blades. Via the usual Bluetooth connection the IMUs communicate with a smartphone. Swim.com<sup>2</sup> is offering a comparable solution in 2018. Their IMU sits at the waist, so that it serves trunks, too. Lenzi (2015) lists commercial wearable IMU devices. They are put onto the back of the head, at the ankle, at the goggles straps, but by far most often they are configured as wristbands, bracelets or watches, so that their place is on the swimmer's wrist. One may conclude that the wrist is the place where the bulk of tracking must be done, simply because of user acceptance. 2018 overviews of swimming trackers or watches<sup>3</sup> confirm this opinion. They advise to choose a device that fits the own activities, swimming included.

Moonley and colleagues (2017) check the dedicated Finis SwimSense<sup>4</sup> and Garmin Swim applications<sup>5</sup>. Both are wrist-based. According to a detailed analysis with competitive and recreational swimmers the devices are good enough for recreational use, but not yet for competitive settings. Camomilla and colleagues (2018) give a very detailed overview of sport tracking IMUs in field use.

On a smartwatch, the monitoring of physical exercise may cohabite with emailing, playing music, and so on. An additional benefit is that a smartwatch cooperates with a smartphone or tablet. Both are more appropriate for inspecting sensor results than the watch with its tiny screen.

One should test whether a watch apps can track swimming style features at an acceptable quality for casual swimmers. CrawlStroke does that.

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<sup>2</sup> <https://blog.swim.com/168-2/>

<sup>3</sup> <https://www.t3.com/features/best-swimming-fitness-tracker>, <https://www.techradar.com/news/best-waterproof-fitness-tracker>, <https://www.techradar.com/news/best-swim-watch>

<sup>4</sup> <https://www.finisswim.com/Swimsense-Live>

<sup>5</sup> <https://www.yourswimlog.com/garmin-swim-watch-review/>

## At the end

At the end the author proposes to look at swimming apps with watch use in the App Store, in order to get some idea about the state of the art there.

Good addresses are:

- *MySwimPro*<sup>6</sup>
- *Swim*<sup>7</sup>
- *SwimIO*<sup>8</sup>

All the apps apply IMUs. They are open to several swimming styles. Productive ideas for appreciating / comparing them are the ease of use (the user experience) and the set of properties that they deliver to their users.

The Apple Watch Training app<sup>9</sup> is maximalist. It serves swimming as one of many physical exercises.

If you want to contrast the - minimalist - CrawlStroke app to an app focusing on a different swimming style, the author's BreastStroke app<sup>10</sup> may be appropriate for the purpose of comparison.

A good argument for swimming apps on the watch is their usability: On everyday devices, they can serve many swimmers inside and outside the pool, not disturbing them when swimming and not handicapping other watch uses.

## References

- Bächlin M, Förster K, Tröster G. (2009). SwimMaster: A wearable assistant for swimmer. In: Ubicomp 2009, Orlando, Florida, USA
- Bächlin M, Tröster G. (2012) Swimming performance and technique evaluation with wearable acceleration sensors. *Pervasive and mobile computing* 8(1): 68-81. <http://doi:10.1016/j.pmcj.2011.05.003>
- Callaway AJ (2015) Measuring Kinematic Variables in Front Crawl Swimming Using Accelerometers: A Validation Study. *Sensors* 2015, 15(5), 1136311386; <https://doi.org/10.3390/s150511363>
- Camomilla V, Bergamini E, Fantozzi S, Vannozzi, G (2018) Trends Supporting the In-Field Use of Wearable Inertial Sensors for Sport Performance Evaluation: A Systematic Review. *Sensors* 2018, 18(3), 873; <https://doi.org/10.3390/s18030873>
- Chollet D, Chaliès S, Chatard JC (2000) A new index of coordination for the crawl: description and usefulness. *Int J Sports Med* 21(1): 54–59
- Dadashi F, Crettenand F, Millet GP, Seifert L, Komar J, Aminian K (2013a) Automatic front-crawl temporal phase detection using adaptive filtering of inertial signals. *J Sports Sci* 31(11): 1251-1260. doi: 10.1080/02640414.2013.778420
- Dadashi F, Millet GP, Aminian K (2013b) Inertial measurement unit and biomechanical analysis of swimming: an update. *Schweizerische Zeitschrift für Sportmedizin und Sporttraumatologie* 61(3): 28–33
- Ganzevles S, Vullings R, Beek, Daanen, H, Truijens M (2017) Using tri-axial accelerometry in daily elite swim training practice. *Sensors*, 17(5): 990.. DOI: 10.3390/s17050990
- Guignard B, Rouard A, Chollet D, Seifert L (2017) Behavioral dynamics in swimming: The appropriate use of inertial measurement units. *Front Psychol.* 8: 383. doi: [10.3389/fpsyg.2017.00383](https://doi.org/10.3389/fpsyg.2017.00383)  
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5348530/>
- Hansen MB (2017) Relationship between trunk acceleration and arm stroke cycle coordination in

<sup>6</sup> <https://itunes.apple.com/de/app/myswimpro/id994386450?mt=8>

<sup>7</sup> <https://itunes.apple.com/us/app/swim-com-smart-swim-tracking/id956030704#?platform=iphone>

<sup>8</sup> <https://itunes.apple.com/us/app/swimio-swim-fitness/id385166726?mt=8>

<sup>9</sup> <https://www.apple.com/ca/apple-watch-series-4/workout/>

<sup>10</sup> <https://itunes.apple.com/de/app/breaststroke-swim-better/id1295629075?mt=8>

- competitive front crawl swimming. Thesis Univ. of Regina.  
[https://ourspace.uregina.ca/bitstream/handle/10294/7739/Hansen\\_Mads\\_200307843\\_MSC\\_KHS\\_Spring2017.pdf?sequence=1&isAllowed=y](https://ourspace.uregina.ca/bitstream/handle/10294/7739/Hansen_Mads_200307843_MSC_KHS_Spring2017.pdf?sequence=1&isAllowed=y)
- James DA, Leadbetter RI, Neeli AR, Burkett BJ, Thiel DV, Lee JB (2011) An integrated swimming monitoring system for the biomechanical analysis of swimming strokes. *Sports Technol.* 4: 141–150
- Lenzi S (2015) Method Development and Validation for Front Crawl Swim Technique Evaluation. Thesis Politecnico di Milano. <https://www.politesi.polimi.it/handle/10589/108737>
- Maglischo E W (1993) *Swimming Even Faster*, Mayfield Publishing Company
- Maglischo EW (2003) *Swimming fastest*. Human Kinetics, Champaign
- McCabe CB, Psycharakis S, Sanders RH (2011) Kinematic differences between front crawl sprint and distance swimmers at sprint pace. *J Sports Sci* 29(2):115–123. doi:10.1080/02640414.2010.523090
- Mooney R, Corley G, Godfrey A, Quinlan LR, ÓLaighin G. (2016) Inertial sensor technology for elite swimming performance analysis: A systematic review. *Sensors* 16(1):18.  
<http://doi:10.3390/s16010018>, <https://www.ncbi.nlm.nih.gov/pubmed/26712760>
- Mooney R, Quinlan LR, Corley G, Godfrey A, Osborough C, ÓLaighin G. (2017) Evaluation of the Finis Swimsense<sup>®</sup> and the Garmin Swim<sup>™</sup> activity monitors for swimming performance and stroke kinematics analysis. *PLoS ONE* 12(2). <http://doi:10.1371/journal.pone.0170902>,  
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5298290/>
- Ohgi Y, Yasumura M, Ichikawa H, Miyaji C (2000) Analysis of stroke technique using acceleration sensor IC in freestyle swimming. In: *Engineering of Sport: Research, Development and Innovation*, eds A. J. Subic and S. Haake (Oxford: Blackwell Science), 503–512
- Pansiot J, Lo B, Yang GZ (2010) Swimming Stroke Kinematic Analysis with BSN. In: 2010 International Conference on Body Sensor Networks, Singapore, 7–9 June 2010; pp. 153–158.  
[http://julien.pansiot.org/papers/2010\\_Pansiot\\_BSN\\_SwimBSN.pdf](http://julien.pansiot.org/papers/2010_Pansiot_BSN_SwimBSN.pdf)
- Psycharakis, SG, Sanders RH (2010) Body roll in swimming: a review. *J Sports Sci* 28(3):229–236.
- Perego P, Andreoni G, Sironi R, Lenzi S (2015) Wearable device for swim assessment : a new ecologic approach for communication and analysis. *MOBIHEALTH 2015*, London.  
<http://eudl.eu/pdf/10.4108/eai.14-10-2015.2261818>
- Sanders RH, Andersen J, Takagi H (2017) The Segmental Movements in Front Crawl Swimming. In: Müller B et al. (eds) *Handbook of Human Motion*. Springer, Cham
- Seifert L, L’Hermette M, Komar J, Orth D, Mell F, Merriaux P, Grenet P, Caritu Y, Hérault R, Doygalecs V, Davids K (2014) Pattern recognition in cyclic and discrete skills performance from inertial measurement units. *Procedia Eng.* 72: 196–201.  
<https://www.sciencedirect.com/science/article/pii/S1877705814005499>
- Wang J, Wang Z, Gao F, Guo M (2016). SwimSense: Monitoring Swimming Motion Using Body Sensor Networks. in: W. Li and colleagues (Eds.): *IDCS 2016, LNCS 9864*: 45–55