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Prediction of Kick Count in Triathletes during Freestyle Swimming Session Using Inertial Sensor Technology

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Featured Application: During sports training, it is relevant to monitor performance parameters, as, for example, stroke and kick count in swimmers. However, as stroke number can be detected by using a wearable "swim stroke meter", the number of kicks is usually detected by acquiring video images, which requires dedicated staff. The availability of a wearable kick-count device may be an opportunity to better monitor swim performance also during individual training.

Abstract: Monitoring sports training performances with automatic, low cost, low power, and ergonomic solutions is a topic of increasing importance in the research of the last years. A parameter of particular interest, which has not been extensively dealt with in a state-of-the-art way, is the count of kicks during swimming training sessions. Coaches and athletes set the training sessions to optimize the kick count and swim stroke rate to acquire velocity and acceleration during swimming. In regard to race distances, counting kicks can influence the athlete's performance. However, it is difficult to record the kick count without facing some issues about subjective interpretation. In this paper, a new method for kick count is proposed, based on only one triaxial accelerometer worn on the athlete's ankle. The algorithm was validated on data recorded during freestyle training sessions. An accuracy of 97.5% with a sensitivity of 99.3% was achieved. The proposed method shows good linearity and a slope of 1.01. These results overcome other state-of-the-art methods, proving that this method is a good candidate for a reliable, embedded kick count.

Keywords: inertial sensors; accelerometer; kick count; training monitoring; sport performance; kick frequency; swimming training

Citation: Bianchi, V.; Ambrosini, L.; Presta, V.; Gobbi, G.; De Munari, I. Prediction of Kick Count in Triathletes during Freestyle Swimming Session Using Inertial Sensor Technology. *Appl. Sci.* **2022**, *12*, 6313. https://doi.org/10.3390/app12136313

Academic Editor: Graziella Scandurra

Received: 23 May 2022
Accepted: 20 June 2022
Published: 21 June 2022

1. Introduction

The production of lightweight, low-cost, and widespread inertial sensors suitable to be embedded in wearable devices has led to their systematic use to monitor, in an unobtrusive way, human posture and motion in several fields such as assisted living [1–6], fitness tracking [7,8], and sports [9]. In the latter, the study of human body movements had great improvements in research, allowing the measurement of performance [10–12]. Several sports have successfully taken advantage of the use of inertial sensors, i.e., gyroscopes, accelerometers, and magnetometers, often included in a unique device identified as the inertial measurement unit (IMU) [13]. First applications of these technologies in swimming date back to the early 2000s when arm stroke motion and fatigue were monitored with a triaxial accelerometer and gyroscope attached to the wrist joint of the swimmers [14]. Since then, several studies reported in the literature have supported coaches in comprehensive monitoring of the performance of their athletes to develop and refine a training model. For example, in [15] numerous kinematic variables related to propulsion, posture, efficiency, and duration/rate of motion in four main swimming phases (wall push-off, glide, stroke preparation, and swimming) were extracted from an IMU attached to the sacrum. An

IMU worn on the wrist or the upper-back was used to discriminate among the different swimming styles in [16,17], whereas in [18] the type of stroke and wall push-offs were detected by deriving pitch and roll angles from an accelerometer mounted on the swimmer's goggles. In [19], a systematic review of the research studies investigating the use of IMU technology for swimming analysis was presented. As it can be seen, several studies centered on the stroke count, stroke rate, stroke phase, acceleration patterns, distance per stroke, stroke identification, lap time, lap count, acceleration, and velocity. However, few researchers have investigated the utility of inertial sensors to quantify kick count. Evidence shows that kick count should be considered during swimming, especially in freestyle, in which high acceleration and velocity can be achieved by adjusting the swim stroke/kick rate [20]. Particularly, the higher kicking favors buoyancy, hydrodynamics, and speed during swimming. In addition, the information on kick counting can allow coaches to define training programs that condition the legs properly to meet the demands of kicking during the competition.

Evaluating a swimmer's kick is difficult when observing above water, due to the water turbulence and mass of white water associated when kicking. Moreover, developing and testing an automated algorithm can be useful, such as by integrating this feature into an embedded system that is able to automatically count the kicks during the training sessions and give direct and rapid feedback to the athletes and coaches.

In the literature, few papers have reported a system capable of automatically counting kicks. In [21] the validity and reliability of the kick count through a gyroscope were evaluated. In this case, four gyroscopes were exploited on the left and right thigh and shank. In [22] the kick-count information was provided using a wireless sensor network that included eight end-devices (EDs) transmitting data wirelessly to an access point connected to a PC through an RS232 connection. The ED was worn on a belt on the back of the swimmer and integrated a triaxial gyroscope and a triaxial accelerometer. Only the data from the latter (limited to one axis) was used for the computation of the kick count, applying a threshold algorithm.

The present study aims to develop and validate an algorithm for the evaluation of the number of kicks performed by a swimmer during a training phase. The algorithm is suitable for embedded and real-time processing on a microcontroller-based device. The system exploits only one sensor (a triaxial accelerometer) worn on the ankle to maximize the athlete's comfort, the system power consumption, and the costs. The implemented algorithm results are independent of how the sensor is worn.

The paper is organized as follows: in Section 2 the methodology is presented, in Section 3 the results are reported and discussed and, finally, in Section 4 conclusions are drawn.

2. Materials and Methods

2.1. Data Collection

To test the capability of the proposed system to accurately recognize the swimming kick gesture in a real scenario, data from 8 professional triathlon athletes (Table 1) were recorded during freestyle swimming training at self-selected speed in a 25 m swimming pool available inside the sports facilities of the University of Parma campus. Each athlete performed two training sessions on two different days and, for each, a total of 400 m was acquired.

Table 1. Gender, age, height, weight, and BMI of athletes recruited in the study.

Athlete Number	Gender	Age (years)	Height (m)	Weight (kg)	BMI
1	M	35	1.84	74.8	22.1
2	M	24	1.75	65.7	21.5
3	M	26	1.75	65.2	21.3
4	M	24	1.75	68.8	22.5
5	F	26	1.66	53	19.2
6	M	31	1.77	71	22.7
7	M	28	1.75	66	21.6
8	M	19	1.78	68	21.5

M = male, F = female, BMI = body mass index.

Since to acquire the data an engineered waterproof device was needed, a commercial device was selected for this purpose. A Garmin Forerunner 735XT device was exploited as the inertial sensor and it was applied to the right ankle of each athlete. It integrates a triaxial accelerometer and a triaxial magnetometer and it is waterproof up to 5 atm. A custom app was designed to access the collected raw data on the Garmin, and the sampling frequency was set to the maximum allowed, i.e., 25 Hz and 1 Hz for the accelerometer and magnetometer, respectively. These values are suitable for a correct evaluation of human movements during swimming [19].

To assess the ground truth, each athlete's swimming session was also recorded by a volunteer outside the swimming pool with a GoPro camera. In Figure 1, a frame from one of the videos is shown.

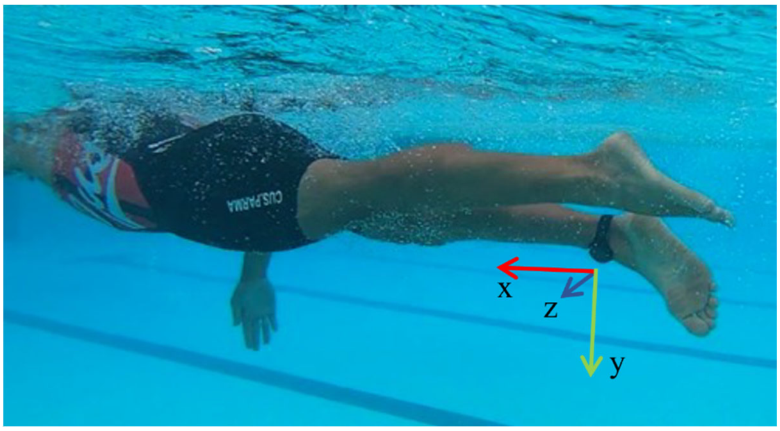

Figure 1. Example of set-up for data collection. The inertial sensor was placed on the right ankle and the ground truth was provided by a recorded video.

2.2. Data Processing

To detect a kick event, data coming from the accelerometer were processed and the Fraden–Neuman algorithm was applied [23]. This algorithm was introduced for the detection of QRS complexes in electrocardiographic (ECG) signals and it is based on applying suitable thresholds on the amplitude and the first derivative of the signal to be analyzed. The choice of a low computational complexity algorithm is advantageous for future embedded implementation and real-time operation. In this work, the thresholds were adapted to the accelerometer signals to detect the kicks of the athletes.

In the first step, the input signal $x(n)$ was rectified so that:

$$y0(n) = |x(n)| \tag{1}$$

It is worth noting that $x(n)$ means a generic input signal without any reference to a particular component (x-y-z axis). Indeed, the algorithm was independently applied to all three components and the related results were evaluated. Then, a low-level clipper operation was applied to have:

$$y1(n) = y0(n) \text{ if } y0(n) \geq \text{th}_1 \quad (2)$$

$$y1(n) = \text{th}_1 \text{ if } y0(n) < \text{th}_1$$

where th_1 was set to 40% of the maximum value of the input signal. This value was experimentally tuned to detect a kick event with maximum accuracy.

Finally, the same threshold th_1 was applied to the $y\_d(n)$ signal, which is the difference quotient of $y1(n)$ computed over the sampling time: if y_d was greater than th_1, a kick event was detected. In Figure 2 an example of the signals involved in the algorithm is shown.

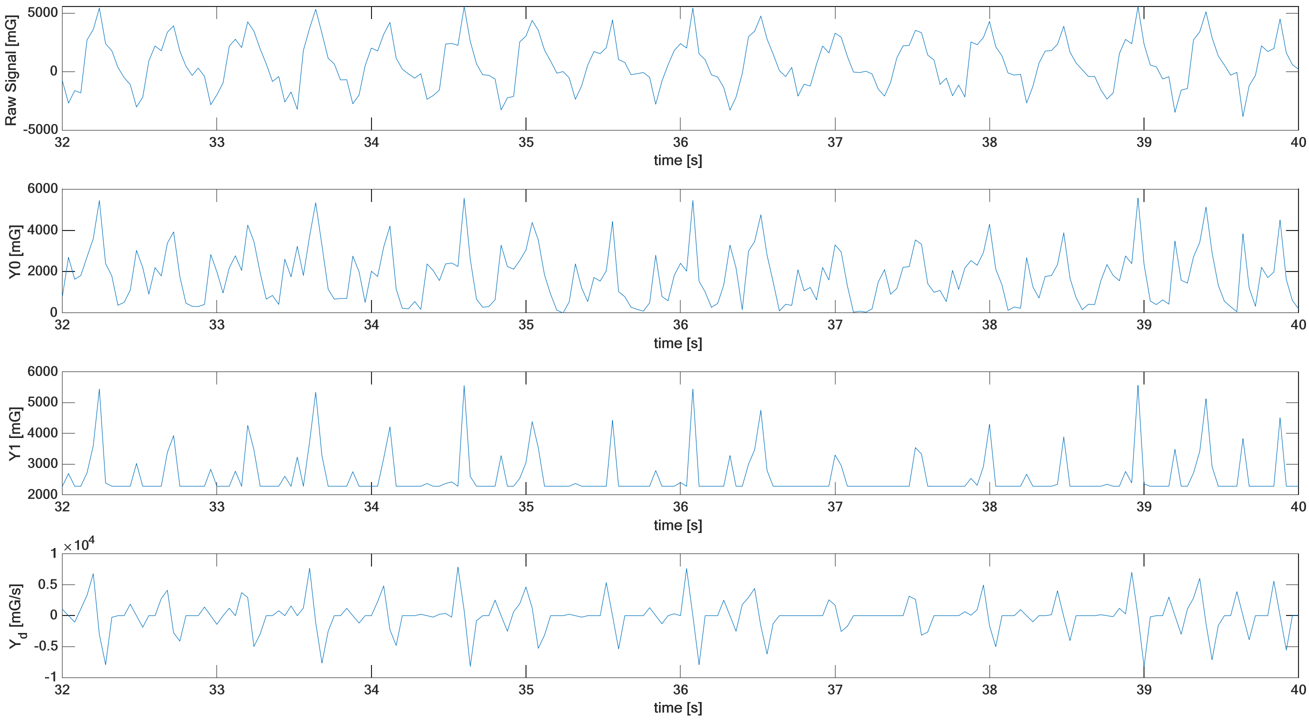

Figure 2. Example of the algorithm signals.

This algorithm was applied to the three axes of the accelerometer to verify which axis or which combination of axes guaranteed the highest accuracy.

Data coming from the magnetometer were exploited to assess when an athlete changed direction during the swim (i.e., to count the laps). In addition, in this case, a threshold-based algorithm was applied. The magnetometer x-axis was considered since it is the one on which the contribution due to the forward movement of the athlete was most concentrated (Figure 1). The change of direction was detected when the magnetic field measured on the x-axis changed the sign.

3. Results and Discussion

In Figures 3 and 4, examples of the captured signals for an athlete are reported.

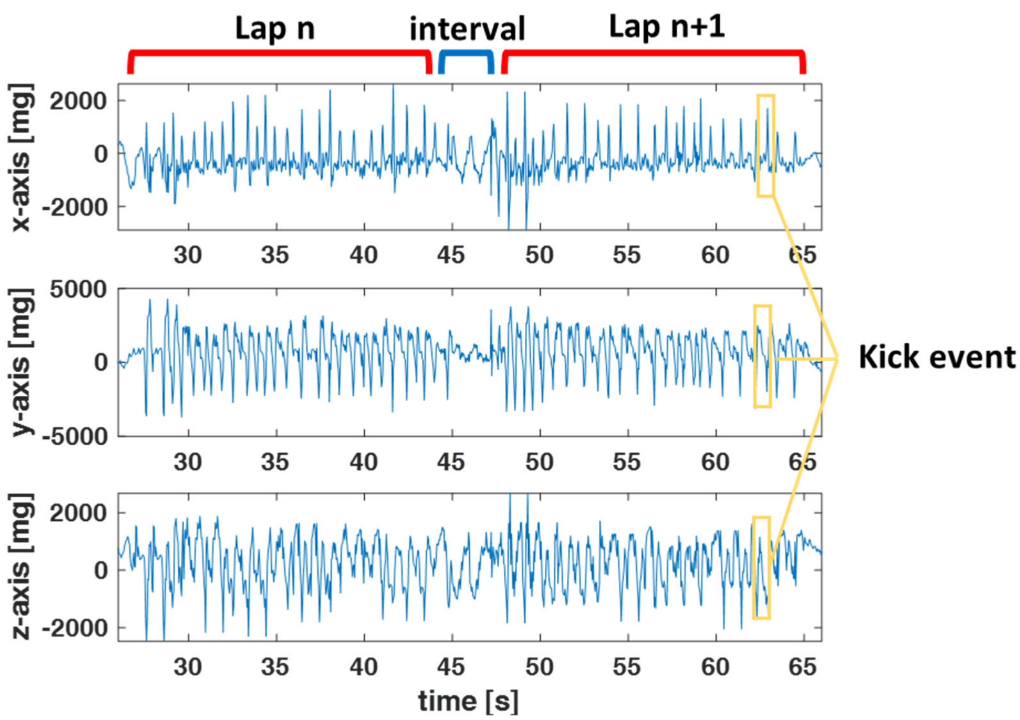

Figure 3. Example of the output of the three-axes accelerometer sensor during two laps of a training session. In the boxes, examples of a kick event on the three axes are underlined.

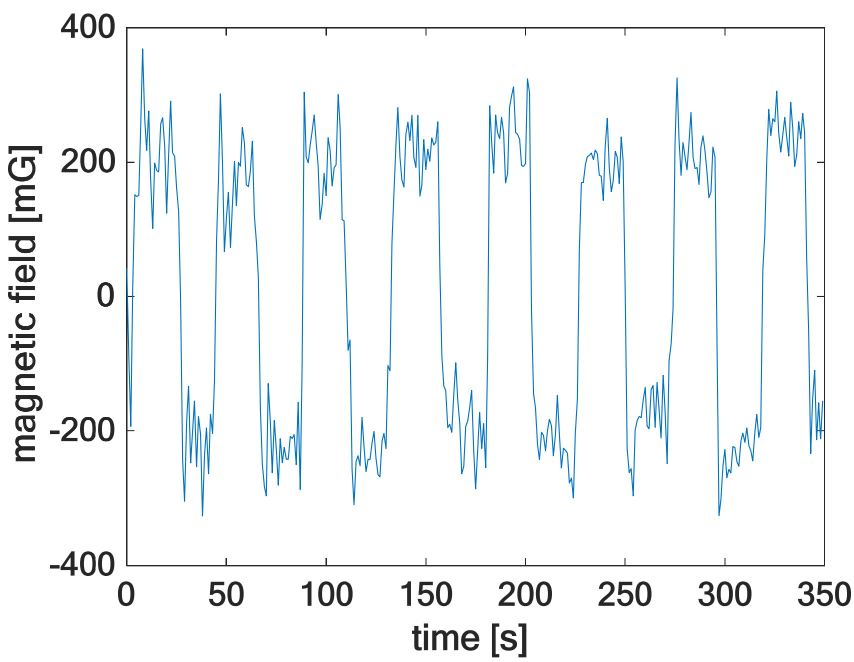

Figure 4. Example of the output of the x-axis of the magnetometer sensor during a training session (16 laps).

In Figure 3, data related to two pool lengths of a swimming session are shown. The kicks are clearly recognizable as a regular repetition of a precise pattern. It is also possible to observe an intermediate period that does not present such regularity, relating to the athlete's change of direction.

In Figure 4, the change of direction is observable as a change in the sign of the magnetometer x-axis signal. It is worth noting that this is independent of how the smartwatch was worn. Indeed, since the watch was fixed to the ankle through the strap, any reversal of the sensor would only lead to an inversion of the signal sign without any change in the output of the algorithm. Detecting when an athlete finished a lap and started a new one was not directly related to the main purpose of this work, which is to present a new method for counting kicks during swimming training sessions. However, it can be useful to better analyze the data obtained and compute some parameters such as, for example, the error obtained in the count considering a predetermined distance (e.g., 100 m).

The modified Fraden–Neuman algorithm was applied to all three accelerometer axes. In Figure 5, the result obtained from processing data shown in Figure 3 is reported. The blue line is the difference quotient $y\_d(n)$. This was computed as the difference between subsequent samples of the signal $y1(n)$ over the sampling time. The red crosses represent a detected kick.

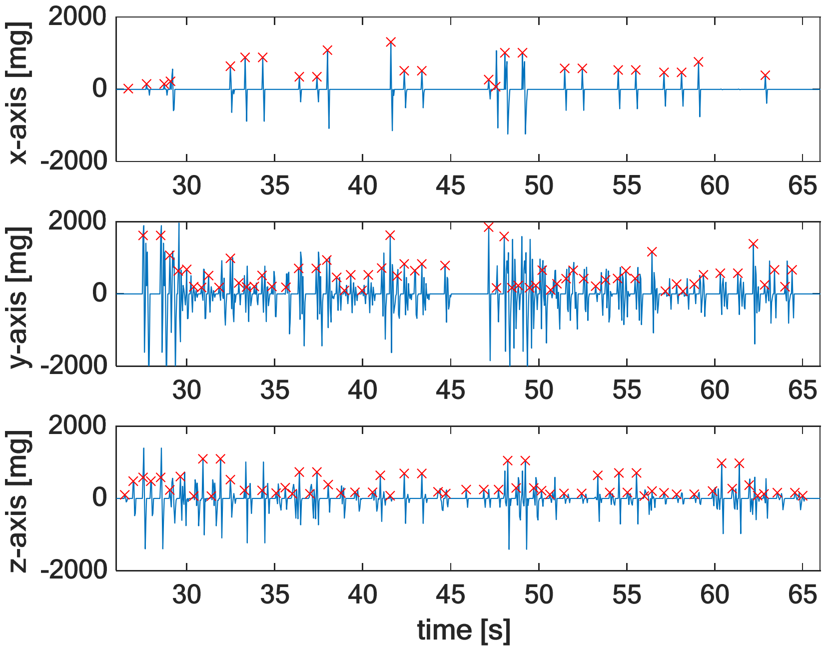

Figure 5. Example of processing with the modified Fraden–Neuman algorithm.

As it can be noted from a preliminary visual analysis, the x-axis resulted in a poor performance in recognizing kicks, whereas in the y-axis and z-axis the kicks were more likely to be detected.

To evaluate the validity of the detection, the recorded videos were examined as they are considered the gold standard. The timing of the video footage was synchronized with the accelerometer raw data, and each kick detected by the algorithm was verified in the video. Moreover, the presence of a kick in the video not detected by the algorithm was also assessed.

To evaluate the algorithm, performance, accuracy, sensitivity, and specificity were considered. Accuracy can be computed as:

$$Acc = \frac{TPs + TNs}{TPs + TNs + FPs + FNs} \tag{3}$$

where TPs are the true positives, TNs are the true negatives, FPs are the false positives, and FNs are the false negatives. TPs refer to the case in which the algorithm detected a kick and the kick was present in the video, whereas TNs relate to the absence of kicks in the processed data and the video. Finally, FPs and FNs are kicks detected by the algorithm that are absent in the video, and kicks not detected by the algorithm but are present in the video, respectively.

Sensitivity (i.e., TP rate) can be computed as:

$$Sen = \frac{TPs}{TPs + FNs} \tag{4}$$

whereas the specificity (i.e., TN rate) can be computed as:

$$Spe = \frac{TNs}{TNs + FPs} \tag{5}$$

It is worth noticing that, due to the nature of the signals involved in the experiments, it was impossible to count the TNs. Indeed, the absence of a kick is a time interval without kick events, and it is impossible to be quantified in a number. For this reason, the specificity was excluded from the performance parameters evaluated.

In Table 2, the accuracy and sensitivity were reported for each axis.

Table 2. Accuracy and sensitivity of the developed algorithm applied on each axis.

Test ID		*x*-Axis		*y*-Axis		*z*-Axis	
Athlete Number	**Test Number**	**Acc [%]**	**Sen [%]**	**Acc [%]**	**Sen**	**Acc [%]**	**Sen [%]**
1	1	69.5	100	98.2	99.80	71.10	99.8
1	2	73.6	99.8	84.3	100	62.80	99.5
2	1	36.6	100	99.4	100	57.6	99.8
2	2	62.8	100	99.6	100	59	100
3	1	42.6	97.5	89.9	94.3	80.4	99.8
3	2	56.2	100	84.7	94.9	56.7	95
4	1	59.3	100	98.5	99.4	83.3	99.3
4	2	54.2	100	98.7	100	93.3	100
5	1	0	0	98.7	99.1	71.7	98.9
5	2	85.7	3.4	98.7	99.8	76.7	99.8
6	1	88.7	99.3	96.6	98.1	41.6	60.3
6	2	86.7	99.3	99.7	99.7	63	67
7	1	61.5	64.9	81.4	100	54.1	54.6
7	2	70.9	99.4	74.7	93.5	65.8	68.4
8	1	0	0	98.6	100	21.1	99.2
8	2	0	0	99.3	99.6	45	99.6

As expected, the y-axis resulted in the best performance, whereas the x-axis and z-axis did not have sufficient accuracy, despite showing a high sensitivity. However, the average accuracy on the y-axis resulted in 93.81%, with an average sensitivity of 98.7%. Notwithstanding, the x-axis and z-axis provided bad results, especially regarding some athletes' tests; these data can be exploited to further improve the results on the y-axis. Indeed, it has been noted that in some cases, when the algorithm failed to detect a kick on the y-axis, it was still correctly detected on one of the other two axes. Following this observation, the performances were evaluated by combining a logic OR with the result of the algorithm applied on each of the three axes. The results are reported in Table 3.

Combining all three axes, an average accuracy of 97.5% was achieved with an average sensitivity of 99.33%. It is worth noting that using the three axes also makes the analysis independent of how the sensor was worn. An average error of two kicks every 100 m was computed among all training sessions.

In Figure 6, the inertial sensors count vs. the gold standard is shown. In the optimal case, the regression line has a slope equal to one and an intercept equal to 0.

Table 3. Accuracy and sensitivity of the developed algorithm applied on each axis and combined with a logic OR.

Test ID		*x*-Axis or *y*-Axis or *z*-Axis	
Athlete Number	**Test Number**	**Acc [%]**	**Sen [%]**
1	1	98.5	99.8
1	2	94.2	99.5
2	1	99.6	99.8
2	2	99.6	100
3	1	90.7	99.8
3	2	87.8	95
4	1	98.9	99.3
4	2	99.3	100
5	1	99.1	98.9
5	2	99.4	99.8
6	1	97.8	98.2
6	2	99.7	99.7
7	1	98.1	100
7	2	94.8	100
8	1	98.6	100
8	2	99.5	99.6

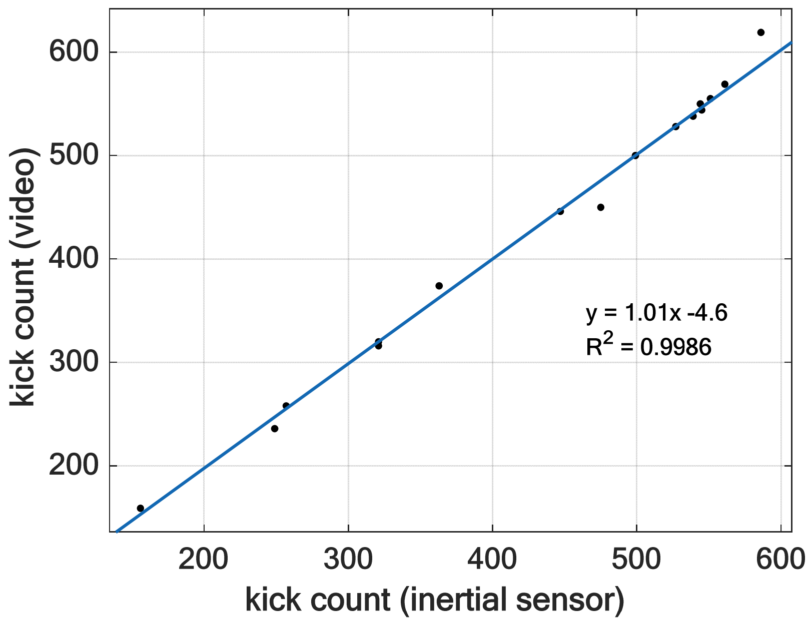

Figure 6. Relationship between the kick count acquired with the accelerometer and the kicks counted in the video footage for each test.

The linear regression was carried out using the MATLAB curve fitting tool, setting a robust fitting method and minimizing the least absolute residuals (LAR). Robust regression is less sensitive to outliers and the resulting model is less dependent on large changes in a small part of the data. As it can be seen, the curve fitting results had a very good linearity with an R^2 of 0.9986. The slope of the line was 1.01, resulting in a relative error in the slope line of 1%.

The result obtained can be compared with results from the literature, showing some advantages. In [21] an algorithm was applied to a gyroscope to demonstrate the validity and the reliability of counting the kicks during a training session using inertial sensors. In this study, accuracy and sensitivity were not reported. However, the authors evaluated the goodness of the fit between the inertial sensor results and the kicks counted in the video footage, resulting in an R^2 of 0.957 with a slope of the line of 0.9101. The relative error on the slope line was 9%, much higher than that found in this study. Moreover, a future embedded implementation that relies on an algorithm based on only an accelerometer can lead to lower power consumption and a less expensive solution. Indeed, the stand-alone accelerometer solutions usually have a lower current consumption and costs concerning both stand-alone gyroscopes and integrated IMUs [24,25].

In [22] a threshold algorithm for the kick count and kick rate based on only accelerometric data was reported. In this case, the accelerometer was worn on the swimmer's back. However, even if the kick rate can be effectively measured with their approach, a very low accuracy (about 49%) in kick count was reported. The authors justified these results with the fact that the swimmers were not in a perfect horizontal position during the training, and their algorithm was very sensitive to the athlete's position with respect to the vertical plane.

Hence, the approach proposed in this study shows a good accuracy with respect to other studies already presented in the literature, and it is prone to be developed as a low cost, low power, and ergonomic embedded solution.

4. Conclusions

In this paper, a new approach for kick count during a freestyle swimming training session is presented. This solution is based on only one accelerometer sensor worn on the athlete's ankle. The algorithm is an adaptation of the Fraden–Neuman algorithm, which is traditionally used for detecting QRS complexes in ECG data. The proposed approach was tested on data collected during the training sessions of eight triathletes on two different days. Video recordings of the training were available as the gold standard. Since the training was performed in a 25 m swimming pool, an engineered waterproof device was needed. For this reason, a Garmin Forerunner 735XT was exploited. In order to comprehensively evaluate the effectiveness of the algorithm using parameters such as accuracy and sensitivity, a synchronization of the raw data collected from the accelerometer and the video footage was performed.

During this study the proposed algorithm was applied independently to all three axes of the accelerometer; it was proven that using the combination of the three results through a logical OR function leads to an improvement in the performance. An average accuracy of 97.5% and an average sensitivity of 99.3% were obtained. Moreover, the linearity of the relationship between the kick count with the proposed method and the ground truth was evaluated, finding an R^2 parameter of 0.9986 and a slope for the line of 1.01. These results improve on the state-of-the-art methods, proving that this work is suitable as a reliable and accurate method for obtaining the kick count during training. In the future, a complete embedded implementation is planned to integrate this work in a stand-alone, ergonomic solution.

Author Contributions: Conceptualization, L.A., G.G., V.B. and I.D.M.; methodology, V.B.; software, V.B.; validation, L.A., V.P. and V.B.; formal analysis, V.B.; investigation, L.A., V.P. and V.B.; resources, G.G. and I.D.M.; data curation, V.B.; writing—original draft preparation, L.A., V.P., V.B. and I.D.M.; writing—review and editing, G.G., V.B. and I.D.M.; supervision, G.G. and I.D.M.; funding acquisition, G.G. and I.D.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Area Vasta Emilia Nord (AVEN) (protocol code 1384/2020/SPER/UNIPR TRIKICK, date of approval 13 April 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data are available on request to the corresponding author.

Acknowledgments: We would like to thank Marco Bassoli for his contribution to the experimental part of this research and the students Gabriele Sechi and Luca Zanantoni for their help in the data analysis. Finally, we are grateful to all the swimmers who participated in this study.

Conflicts of Interest: The authors declare no conflict of interest.

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