Efficient Accelerometer-Based Swimming Exercise Tracking

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***Abstract*—The study concentrates on tracking swimming exercises based on the data of 3D accelerometer and shows that human activities can be tracked accurately using low sampling rates. The tracking of swimming exercise is done in three phases: first the swimming style and turns are recognized, secondly the number of strokes are counted and thirdly the intensity of swimming is estimated. Tracking is done using efficient methods because the methods presented in the study are designed for light applications which do not allow heavy computing. To keep tracking as light as possible it is studied what is the lowest sampling frequency that can be used and still obtain accurate results. Moreover, two different sensor placements (wrist and upper back) are compared. The results of the study show that tracking can be done with high accuracy using simple methods that are fast to calculate and with a really low sampling frequency. It is shown that an upper back-worn sensor is more accurate than a wrist-worn one when the swimming style is recognized, but when the number of strokes is counted and intensity estimated, the sensors give approximately equally accurate results.**

***Index Terms*—Accelerometer, efficient methods, human activity tracking, swimming**

I. Introduction and Related Work

It is known that physical activity can prevent chronic diseases and of course improve physical health. Therefore it is important to motivate people to exercise. Technology can motivate people and there are devices and methods available to help training in several sports such as running [1], golf [2], snowboarding [3] and swimming [4]. Also in our study methods and technologies to assist swimmers are presented. Using presented methods it is possible to keep track about training hours, to estimate the efficiency of training and analyze techniques. This allows a person to fully concentrate on training and there is no need to worry that he or she does not remember the training program after wards.

This article concentrates on studying the following three research questions:

1) how swimming exercise can be tracked efficiently;
2) how reduction of sampling frequency affects tracking accuracy;
3) comparing different sensor placements.

Swimming exercise is tracked by studying the following four questions: (1) how a swimming style can be recognized, which enables the forming of an automatic activity diary, (2) how turns can be counted, therefore, if the length of the swimming pool is known, it is possible to tell the average swimming velocity per lane and the swimming distance, (3) how strokes can be counted, which enables the recognition of the number of strokes per lane and analyzing of swimming technique and (4) how the intensity of the training can be recognized, which enables the estimation of energy expenditure. The swimming tracking methods presented in the study are designed for light applications which do not allow heavy computing and therefore they need to be efficient. To keep the battery usage of the final product as low as possible, it was tested what is the lowest frequency of the accelerometer that can be used and still track exercise with high accuracy. In the previous studies (see e.g. [5], [6]), it is claimed that the lowest frequency that can be used to recognize human activities reliably is 20Hz. In this study, it is tested if even lower sampling rates can be used. In addition, to keep tracking as efficient as possible, the tracking is based on the information of one accelerometer only. However, in this study, the data is collected using two accelerometers to compare how the placement of the accelerometer affects the results.

Bächlin et. al presented SwimMaster in [7]. SwimMaster is an accelerometer-based swim assistant that can for example be used to recognize the swimming velocity per lane, body balance and body rotation. SwimMaster gives information to a swimmer using three actuators and collects data using three sensors. 3D accelerometers were attached to the upper and lower back and to the swimmer's right wrist. The main difference in our study and SwimMaster is that apparently in [7] the number of turns and strokes was recognized from freestyle swimming only and therefore there was no need to recognize swimming style while in our study three swimming styles were used. In different swimming styles, strokes and turnings are performed in a different way, so they cannot be recognized using one model only.

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In [8] methods to track free-weight exercises automatically are presented. In the study, the type of exercise and also the number of repetitions are automatically recognized. The recognition is done based on the data of two accelerometers, one attached to the glove to track hand movements, and another to the waist to track the body posture. The tracking is done in two stages: first, the type of exercise is recognized, and secondly, the number of repetitions. The achieved results are good, the type of exercise is recognized using Naive Bayes Classifier with an accuracy of 95% in the user-depended case and with an accuracy of 85% in the user-independent case. Using the peak count the number of repetitions was recognized with around 5% miscount rate.

As mentioned before, one purpose of the study is to form an automatic activity diary about performed swimming exercises. Automatic activity diaries have also been studied before, for example in [9], [10]. In these studies, different sport exercises are recognized from accelerometer data, but unlike in this study, the received information about the type of exercise is not used to extract more parameters about the exercise.

The paper is organized as follows: Section II presents the used data set. Section III introduces used methods and Section IV evaluates the accuracy of the proposed method. Finally, the conclusions are in Section V.

II. Data Collection

In this study, the data were collected using accelerometers designed by MSR Electronics GmbH [11]. Used data loggers are very small and light, they weight only 18 grams, and include 3D accelerometer, a temperature sensor, a humidity sensor and a pressure sensor. In this study, only acceleration data were used. The data were collected with the frequency of 50Hz. Two accelerometers were used, one was attached to the wrist and the other to the upper back of the subject. The tracking was done based on the data of one accelerometer only. Nevertheless, data were collected using two sensors because, as mentioned above, one purpose of the study was to compare how different sensor placements affect the results.

Two different data sets were collected from each person. The first data set consists of freestyle and breaststroke swimming, and the swimmer was told to perform each swimming style using three different velocities: slow, semi-fast and fast, respectively. Also the oxygen consumption of the subject was measured during the exercise using indirect calorimetry to define the energy expenditure of the performer. This information was used to label the collected data into different intensity levels. The data were collected from 11 persons including both men and women but also amateurs and professionals, see Table I for more details.

The second data set consists of three different swimming styles: freestyle, breaststroke and backstroke swimming. In this data, set the subjects were allowed to choose the swimming speed freely. In this case, the oxygen consumption was not measured because backstroke swimming cannot be performed while the oxygen consumption measuring unit is attached to a person's back. This data were collected from the same 11 persons as the first data set.

TABLE I
Information about subjects (mean and standard deviation).

	Men (n=7)	**Women (n=4)**
Age (years)	26.1 ± 10.2	25.5 ± 11.2
Height (cm)	180.5 ± 1.8	176.0 ± 4.2
Body mass (kg)	75.9 ± 6.0	66.3 ± 10.7

III. Aim of the Study and Methods

The aim of the study is to compare different sampling frequencies and conclude how accurately swimming exercise can be tracked using only acceleration data and low frequency signals. Tracking is done by recognizing the swimming style, the intensity of swimming and the number of turns and strokes. This information can then be used to define the swimming speed, swim distance and to estimate the energy expenditure. The methods used in this study are designed for appliances that do not allow heavy computing; therefore, the used methods were simple and fast to calculate. It was also tested how the placement of the sensor affects the results.

The tracking is done in three phases: first, swimming style and turns are recognized, secondly, the number of turns is counted and finally, the intensity of exercise is recognized.

A. Classification

Both the recognition of swimming style and intensity are recognized using simple classification methods. In fact, only linear and quadratic classifiers (LDA and QDA) were used (for more details see [12]). The classification was done using the sliding window technique and the appropriate window size was decided based on various tests. It was noted that the best classification accuracies for the data of wrist- and upper back-worn accelerometers were obtained using about two seconds long windows with a slide of 0.5 seconds between two sequential windows. Therefore the system classified the ongoing activity at intervals of a half a second. From each window, features were extracted and the classification was done based on these features. The methods presented in this study are efficient; therefore the features used in the classification process are simple and fast to calculate, such as standard deviation, mean and median.

As mentioned above, the classification algorithms are used to detect the swimming style and intensity, but also turns. In [7], it is claimed that turns can be detected by recognizing strongly increasing slopes caused by the wall-strikes from the acceleration signal. It was noted that, in the case of our data set, this method was not possible to use. In some cases wall-strikes did not cause strongly increasing slopes (see Fig. 1) because there seems to be more than one way to perform the turning. As the Fig. 1 shows, in some cases, the shape of the acceleration signal caused by the turn is greater than the shape caused by strokes, and in some cases, it is smaller. Therefore, turns cannot be recognized using peak count, either. It seems

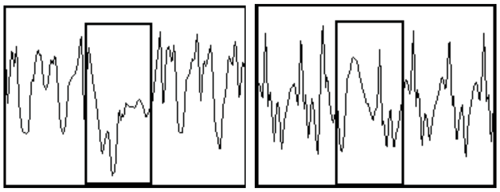

Fig. 1. Examples of differently performed turns.

that the wall-strike style, and thus, the turning style seems to depend on the performed swimming style, and especially the professional swimmers tend to turn very differently from the amateurs. Therefore, to recognize turns, *turn* was selected as a separate class to recognize in the classification process.

B. Peak Count

In this study peak count is used to calculate the number of strokes. Simply, a peak count-level is chosen based on the training set and then it is counted how many times the acceleration signal crosses this level. This number is considered as the number of performed strokes. To avoid false positive results, only crossings with a distance bigger than a predefined limit are counted. The limit is chosen based on how fast subjects can perform two sequential strokes.

IV. Experiments

The tracking of swimming exercise is done in this study by dividing the problem into three pieces. Therefore, this experiments section consists of three parts: in Section IV-A, the results of recognition of swimming style and turns are presented, in Section IV-B, the results of counting the number of strokes are presented, and finally in Section IV-C, the results of estimating the intensity of swimming are presented. In every section, it is studied how the reduction of the sampling frequency affects the accuracy of the results. In addition, to compare sensor placements, each of these studies is done using a wrist-worn sensor and upper back-worn sensor.

A. Recognition of Swimming Style

As mentioned in Section III-A, the recognition of swimming style and turns is done by classifying data into four classes: *freestyle*, *breaststroke*, *backstroke* swimming and *turns* using QDA classifier. Features were extracted from each acceleration channel: mean, standard deviation, minimum, maximum, ratio of mean crossings and different percentiles but also a correlation between different acceleration channels. A total number of 42 features were calculated. The most suitable of these were selected using a forward-selection method and used in the classification process.

To test how the frequency of the acceleration signal affects the accuracy of the results, the results are calculated from 5, 10 and 25Hz signals. These signals are created from the original 50Hz signal by removing points, for example a signal of frequency 10Hz was created from the original signal by leaving only every fifth point left.

TABLE II
THE RECOGNITION RATES OF SWIMMING STYLES USING DIFFERENT SAMPLING FREQUENCIES.

Hz / Sensor	**5**	**10**	**25**
Wrist	88.5%	88.9%	89.8%
Back	95.1%	95.4%	95.3%

TABLE III
THE CLASSIFICATION RESULTS OF WRIST-WORN SENSOR USING SIGNAL OF FREQUENCY 5HZ.

True class / predicted class	**Free-style**	**Breast-stroke**	**Back-stroke**	**Turn**
Freestyle	**90.8 %**	0 %	2.3 %	6.8 %
Breast-stroke	2.5 %	**92.6 %**	1.0%	3.9 %
Back- stroke	1.7 %	1.7 %	**88.8 %**	7.8 %
Turn	5.2 %	6.9 %	6.2 %	**81.7 %**

Sensor data were first modified to a desired frequency (5, 10 or 25Hz) and then pre-processed. Smoothing was done using a moving average (MA) filter and the same weight was given to each point [13]. This way, the number of disturbances could be reduced and the signal became smoother and easier to handle. Different lengths of the windows of MA were used with different sensors and different sampling rates. However, in general, it can be said that to obtain the best results the length of the MA was bigger when a wrist-worn sensor was used compared with the use of an upper back-sensor. Also other filtering algorithms were tested, such as median [14], Butterworth [15] and Savitzky - Golay smoothing filter [16], but MA gave the best results.

1) Results: The recognition is done using data from two different sensors, wrist-worn and back-worn 3D accelerometers. The results using different sampling frequencies are shown in Table II and more detailed results from 5Hz data are presented in Tables III and IV. Classification was done user-independently by using the data of one person in turn in testing and the rest of the data in training.

2) Discussion: The results show (see Table II) that the accuracy of the back-worn sensor is superior compared to the wrist-sensor; over 95% of windows are classified correctly when the back-worn sensor is used. Still, both sensors give very accurate results. The results of the back-worn sensor are better than the results of the wrist-worn sensor probably because the upper back as the placement is more stable and not as susceptible to disturbances as the wrist.

Perhaps, the most interesting finding about the results is that it seems that the reduction of frequency reduces the accuracy of recognition only slightly, while the applications that work with a small frequency use must less battery and computation power than high frequency applications. This means that the suggested methods are efficient and suitable for light applications.

The more detailed results presented in Tables III and IV show that each swimming style can be recognized with a high

TABLE IV
THE CLASSIFICATION RESULTS OF UPPER BACK-WORN SENSOR USING SIGNAL OF FREQUENCY 5HZ.

True class / predicted class	**Free-style**	**Breast-stroke**	**Back-stroke**	**Turn**
Freestyle	**96.1 %**	0 %	0 %	3.9%
Breast-stroke	0 %	**96.7 %**	0 %	3.3%
Back- stroke	0 %	0 %	**97.1 %**	2.9 %
Turn	2.1 %	5.5 %	2.5 %	**89.8%**

accuracy, whereas the recognition rate of turns is somewhat lower. However, the windows that are incorrectly recognized as turns are located near the places where turns are performed. Similarly, false negative results of class *turn* are as well located near the places where turns are performed. Actually, in most of the cases at least part of the performed turn is recognized correctly. In fact, only two turns were not recognized at all when the wrist-worn sensor was used and all turns were recognized using the upper back-worn sensor, although, the wrist-sensor produced some false positive results.

B. Counting Strokes

The number of strokes was counted using the peak count-method presented in Section III-B. Since the performed swimming style can be recognized with a high accuracy, as shown in the previous section, the accuracy of stroke calculation can be improved by defining different peak count-levels for different swimming styles. In addition, the results of Section IV-A show that it is possible to recognize the number of swam lanes, and therefore, stroke-number calculation was done separately per every lane.

1) Results: The number of performed strokes was detected separately from the data of wrist-worn and back-worn sensors and the results are presented in Table V.

In the case of the wrist-sensor data, the strokes of freestyle swimming and backstroke swimming are recognized from z-axis sensor and breaststroke swimming style from x-axis accelerometer data. The strokes of freestyle and backstroke swimming styles were detected by calculating how many times the signal value $z > percentile_S$, where $percentile_S$ is the S-percentile of the z-axis signal during one lane and S is different to both swimming style. Whereas, the number of strokes of breaststroke swimming was detected by counting how many times $x < percentile_S$, where $percentile_S$ is the S-percentile of the x-axis signal during one lane and value S was defined using separate training and test sets.

In the case of upper back-sensor data, the strokes of freestyle swimming and backstroke swimming are recognized from y-axis sensor and breaststroke swimming style from x-axis accelerometer data using similar equations.

2) Discussion: The study shows that both sensor placements that were tested are practically as accurate and using the sampling frequency 25Hz, the number of performed strokes can be recognized almost perfectly using peak count. Using the back-worn sensor a few strokes are not recognized but still the misdetection rate is less than 1 %. The stroke counting was also tested using the sampling frequencies 5Hz and 10Hz. The test shows that periodic human actions can be recognized with a high accuracy even with low frequency signals. The problem with 5Hz signals is that most of the false negative results were caused by one or two persons. Therefore, the strokes of some subject were very difficult to count, while most caused no problems. This means that if the swimming style of some subject is not known, it is wise to use a frequency greater than 5Hz to recognize strokes. For instance, the usage of 10Hz gives more accurate results.

C. Swimming Intensity Estimation

Subjects oxygen consumptions was measured while they were performing freestyle and breaststroke swimming using three different speeds: fast, semi-fast and slow. During this exercise oxygen consumption was measured. The purpose of this study was to estimate the intensity of these exercises based on the acceleration signal by classifying data into three classes. To be able to classify the data, the data were labeled. The simplest way to label this data into three classes was to use class labels $fast$, $semi-fast$ and $slow$. The problem is that subjects have self-determined which speed they for example consider slow. In many cases, it seemed that the subject's oxygen consumption was about the same during slow and semi-fast swimming, meaning that velocities during these exercises have been around the same. Therefore, the data had to be labeled using some other method. According to Harvard Medical School's Harvard Health Publications [17], freestyle swimming that consumes between 8 to 11 METs can be considered semi-fast swimming. Accordingly, the data were labeled into three classes: (1) oxygen consumption less than 8.0 METs, (2) oxygen consumption between 8.0 and 11.0 METs (3) oxygen consumption greater than 11.0 METs.

1) Results: The results are shown in Table VI. To test how different sampling rates affect classification accuracy, three different sampling rates were used: 5Hz, 10Hz and 25Hz. In each case, LDA classifier was used. Classification was done user-independently by using the data of one person in turn in testing and the rest of the data in training.

2) Discussion: The classification was done using the data that were divided into three intensity classes based on oxygen consumption. The problem in this procedure is that class boundaries are strict. When the energy expenditures of two exercises are compared the difference can be really small measured in METs, but still they can belong to different intensity classes. Actually, in this study most of the falsely classified instances are cases where energy expenditure is close to the class boundary. Still, the study shows that the used method can be employed to estimate the intensity of the exercise with a high accuracy (see Table VI).

What is noticeable is that recognition can be done accurately using low frequency signals, as was the case in studies of Sections IV-A and IV-B too. Actually, the best recognition rates using the upper back sensor were obtained when the sampling frequency 5Hz was used. This shows that there is no

TABLE V
STROKE COUNT USING WRIST AND BACK SENSORS.

Data set / Sport	**Wrist 5Hz** Correct / Uncorrect	**Back 5Hz** Correct / Uncorrect	**Wrist 10Hz** Correct / Uncorrect	**Back 10Hz** Correct / Uncorrect	**Wrist 25Hz** Correct / Uncorrect	**Back 25Hz** Correct / Uncorrect
Freestyle	284 / 6	290 / 0	288 / 2	290 / 0	288 / 2	290 / 0
Breaststroke	390 / 2	389 / 3	392 / 0	389 / 3	392 / 0	388 / 4
Backstroke	363 / 9	360 / 12	373 / 0	370 / 3	373 / 0	372 / 1
Total	1038 / 17	1040 / 15	1053 / 2	1049 / 6	1053 / 2	1050 / 5

TABLE VI
ACCURACY OF INTENSITY ESTIMATION USING DIFFERENT DATA SETS

Data set / Sport	**Wrist 5Hz**	**Back 5Hz**	**Wrist 10Hz**	**Back 10Hz**	**Wrist 25Hz**	**Back 25Hz**
Freestyle	85.9%	85.0%	83.3%	79.3%	86.5%	83.3%
Breaststroke	91.8%	90.2%	90.5%	89.2%	94.3%	88.7%
Total	88.9%	87.6%	86.9%	84.3%	90.4%	86.0%

need to use high frequency signals in studies where intensity is estimated.

V. CONCLUSIONS

In this study, swimming exercises are tracked based on low frequency acceleration data. Tracking is done in three phases: first, the swimming style and turns are recognized, then, the number of strokes are counted, and finally, the intensity of exercise is estimated. It is shown that these can be done with high accuracy using light methods and a low sampling frequency. Therefore, the presented methods can be used in applications that do not allow heavy computation. The study also shows that tracking can be done using wrist-worn or upper back-worn sensors. In the case of the swimming style recognition, the upper back-sensor is more accurate but when the number of strokes was calculated and the intensity of exercise was estimated, the sensors were equally accurate.

In the most of the earlier studies, high frequency acceleration signals are used (for example [10], [18], [19]), but for example in [5], [6], it is claimed that the lowest frequency that can be used to track human activities reliably is 20Hz. In our study, even lower sampling rates were used to track swimming exercise. According to our study, even 5 Hz can be enough to recognize the type and intensity of human activity and using 10Hz more detailed human actions can be recognized. The results show that different frequencies would be wise and interesting to test in other studies, too; a low sampling rate does not necessarily mean a low tracking accuracy.

In the case of the recognizing the swimming style, the recognition of non-swimming activities are not considered in this study, so no matter what person is doing it is classified as one of the four activities studied in the study. However, if the back-worn sensor is used, then it is easy to recognize most non-swimming activities based on gravity. Therefore, if the gravity is not approximately perpendicular to z-way acceleration, it can be concluded that a person is not swimming and the activity can be considered as non-swimming activity.

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