ISwimCoach: A Smart Coach guiding System for Assisting Swimmers Free Style Strokes

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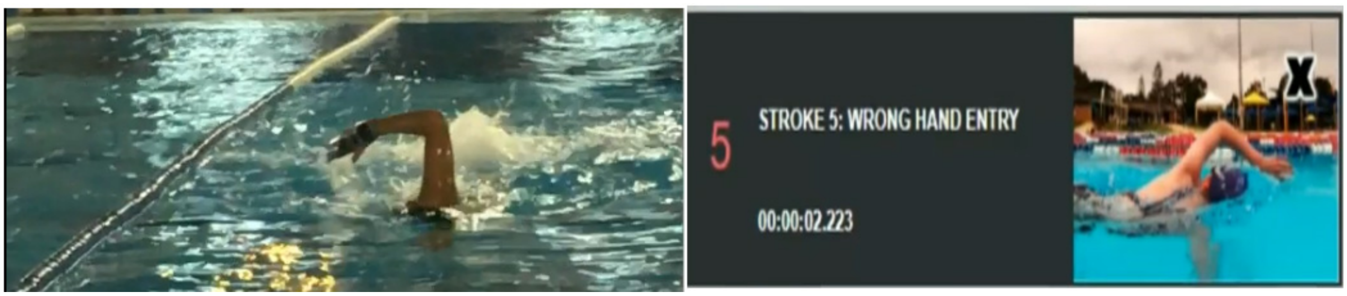

Figure 1: iSwimCoach: a system for analyzing swimmers stroke performance and coach guidance

ABSTRACT

In sports, coaching remains an essential aspect of the efficiency of the athlete's performance. This paper proposes a wrist wearable assistant for the swimmer called iSwimCoach. The key aim behind the system is to detect and analyze incorrect swimming patterns in a free crawl swimming style using an accelerometer sensor. iSwimCoach collects patterns of a swimmer's stream which enables it to detect the strokes to be analyzed in real-time. Therefore, introducing quick and efficient self-coaching feature for mid-level athlete to enhance their swimming style. In our research, we were able to monitor athlete strokes underwater and hence assist swimming coaches. The proposed system was able to classify four types of strokes done by mid-level players (correct strokes, wrong recovery, wrong hand entry and wrong high elbow). The system informs both the swimmer and the coach when an incorrect movement is detected. iSwimCoach achieved 91% accuracy for the detection and classification of incorrect strokes by a fast non expensive dynamic time warping algorithm. These readings analyzed in real-time to automatically generate reports for the swimmer and coach.

CCS CONCEPTS

• **Human-centered computing → Gestural input**.

KEYWORDS

Wearable Systems, Sensors, Human activity recognition, gesture classification

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1 INTRODUCTION

According to information on healthy swimming and recreational water, swimming is the fourth most popular recreational activity in the United States. Another study stated that 49.2% of the United States swimmers are swimming in natural waters (Eg. Lakes, rivers, streams or oceans) each year [15]. According to physical activity council Report[1], swimming acts as an inspirational sport for ages ranging between 6 and 65+. Only 719 entries out of 2400 entries are qualified to enter the Junior competition of International Swimming Federation (FINA) World Championship (WC)[23].

Swimming is a good activity workout because the body needs to be moved as a whole against the resistance of water[16]. Coaching the swimmers with the innovative technologies is aiding to avoid injuries that happened during swimming [4, 6, 11, 12]. The British journal of sports medicine stated that 91% out of 80 young elite swimmers 13-25 years old are reported as cases of shoulder pain due to wrong hand and arm movements[18]. In order to prevent injuries better communication among the swimmers and coaches is required, as well as the usage of the appropriate strokes techniques[2]. The

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swimming coach plays a vital role in the training process, with responsibility for incitement a positive change in a swimmer's performance.

Performance analysis can be typically defined as the necessary provision of objective feedback to swimmers. A precise real-time monitoring during the swimming of a certain swimmer is of essential importance to meaningfully improve style and performance [20]. However, many challenges face swimming real time systems like speed of analysis and feedback sent to swimmers [13]. In addition to the tracking of many swimmers inside water is a cumbersome task for the coaches standing around the pool [5].

In this paper, we presented a system that focuses on detecting and analyzing incorrect strokes in front crawl swimming style. Incorrect strokes are classified into three types, First, "wrong hand entry" as shown in figure 2 (a). In wrong hand entry the wrist of the swimmer is bend towards the surface of the water. Second, "high elbow" is a gesture where the elbow preform an angle of inclination more than 45 degree as shown in figure 2 (b). Thirds, is "Wrong exit" where the user move his hand vertically direct without having a full circle on body toe. Figure 2 (c) shows the details for the wrong gesture movement. The coach can be acutely aware of wrong movements while the swimmer's arm is above the water as shown in figure 1. The challenge of noticing the wrong movement is when the arm is under the water due to other factors like the light refraction on the water surface. Therefore, the system can give the swimming coaching community a significant interest and enhancement. iSwimCoach helps to improve swimming strokes to moderate pace in a relaxed fashion. In addition to being able to swim fast and accommodate to enter competitions easily without getting exhausted or worrying about the incorrect strokes. The main contribution of this paper lies in achieving an acceptable accuracy for detection and classification of incorrect strokes through accelerometer sensor using the dynamic time warping (DTW) algorithm. These readings analysed in a real-time to automatically generate reports for the swimmer and coach.

Swimming research has matured slowly due to difficulties caused by the use of new technologies into water. Several studies already presented attempts to adapt accelerometer and gyroscopes in swimming sports [17][10][8]. iSwimCoach is a way to focus on the swimming strokes error using accelerometer sensors. The system notifies the swimmer and coach with details about the error done in a real-time.

The main contribution in this system is that we developed a system that was able to classify between four types of stroke styles in crawl swimming. The system was capable of showing online reports to the coach and send feedback to the swimmer inside the water to enhance his style.

2 RELATED WORK

New pervasive devices strongly affect the world of sports. The most well-known wearable systems nowadays are used in monitoring the athletes performance widely. Regarding the swimmers, there are small devices available which are used to count the numbers of swim strokes, measure the lane time and monitoring the heart rate [8][9] . Some of them can be extracted from the sensor signal by using pattern recognition techniques [22]. There has been several researches that addressed the usage of assistive technologies and sensors in swimming. "Swimmaster" [4] is a system properly introducing a wearable assistant for elite swimmers that assist in swimming. The system typically uses acceleration sensors with micro-controllers and feedback interface modules.Wearable devices were attached to the upper and lower back. Their main aim was to improve the swimmer's performance by using the sensor's readings, which was analyzed to monitor the stroke time and velocity. Improve the body balance and to give a feed back for achieving the desired goal. They used a video camera for feedback, but a challenge arose as the camera could not record more than three meters away from the swimmer. This showed less efficiency compared to using the accelerometer sensor.

Inertial sensor technology for elite swimming is a system described by Robert et al.,[14] that uses accelerometer and gyroscope sensors along with two cameras to detect the position of the swimmer under and above the water. This aid in detecting the velocity and the angle of the joints of the swimmer. The system aims to improve the performance of the swimmer using accelerometer and gyroscope sensors as it uses real-time feedback. In the pre-processing they used the low-pass filter, threshold and peak detection algorithm to determine which stroke that should be used in calculations. The processing Hidden Markov Model and neural network are used. The reported accuracy is 88.9% which made on 12 swimmers each completing 400 meters.Validation trial of an accelerometer-based sensor platform for swimming[7] is a system aiming to measure the activity levels of the swimmers in the natural environment, in addition to get analysis of the swimmers strokes. Data are collected using an accelerometer and a video-camera. The challenges are that the accelerometer hardware device must be comfortable for the athlete to make him swim without obstacles. In the pre-processing data is filtered using hamming filter to remove the vibration signals.Distinguishing the swimming tumble turn using acceleration data [19] aims to improve the turn over of the free style-swimming stroke in a real-time mode using accelerometer sensors. In pre-processing data is filtered using Butter-worth filter, also they used zero crossing algorithm to identify the stroke in the Y-axis. Investigating forward velocity and symmetry in freestyle swimming using inertial sensors [21] aims to improve the performance of the swimmers using accelerometer sensors. In pre-processing the data was filtered using the high-pass filter.

3 PROPOSED SYSTEM

We proposed a novel system that classifies and recognize the strokes of the swimmer and generate real-time feedback and performance reports. The data is collected by fixing the mobile device on the wrist of the player to collect accelerometer sensor readings of swimmers strokes. The smartphone was fixed by a medical wrist hand support brace for experimental testing purposes.

The collected readings pass through a pre-processing phase to get better results by using a low-pass filtration (LPF) technique. The filtered data are transferred to the cloud storage through the GSM network, for the server-side to analyze the readings. The server-side uses the FastDTW algorithm for classifying the stroke either correct or one of the known mistakes. The classified data is then stored

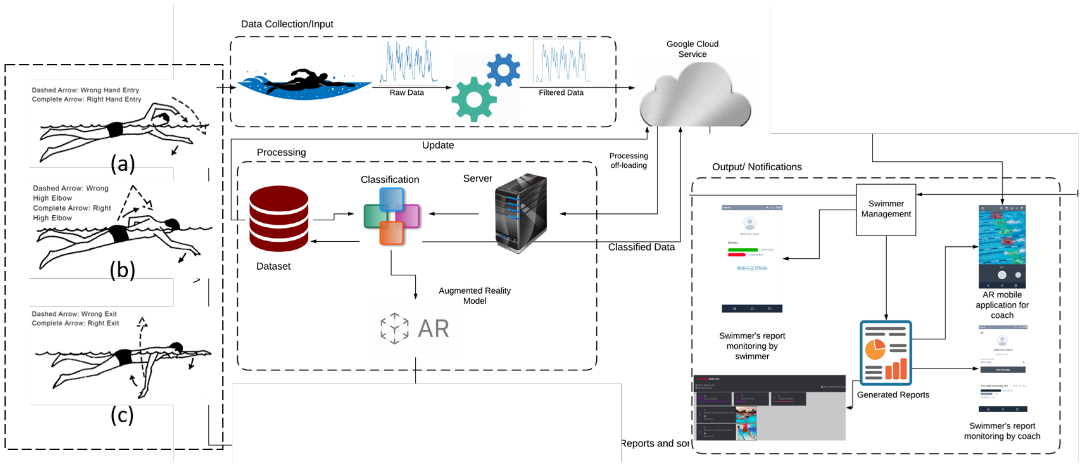

Figure 2: iSwimCoach system overview, Swimmers send raw data for classification, reports generated to the coach and vibration patterns fired to swimmers.

back to the cloud storage for notifications to be sent to the athlete and the coach. The output from the system varies according to the logged-in user to ensure the most enormous amount of benefit to each one. Each swimmer can be informed by his mistake by a vibration signal fired by the mobile on his wrist. A web screen application shows a live full statistics for the whole swimmers to the coach. The web application shows each swimmer count of strokes, the duration for each stroke and also mistake shape. Figure 2 shows an overview of the proposed iSwimCoach system.

A smartphone with a built-in accelerometer sensor is being used to obtain the input readings. The recorded data are a stream of accelerometer readings (ax, ay, az) and timestamp. The collected sensor readings represent the sequence of the stroke across time. The collected stream subsequently filtered using a low-pass filter(LPF) [3] to remove all noises.

The filtered stream divided into several windows were each window represents a stroke of 150 points.Each window stroke then moves to be interpolated and extrapolated before entering the classification phase with linear interpolation method. Both processes are executed on the testing window and the dataset template to make sure that both have an identical number of points before entering the classifier algorithm in the processing section. Based on empirical study, all windows and templates are interpolated to 240 points if they are more and extrapolated to 240 points if they are less.

The output data from the pre-processing section can be represented in separated strokes. This section is to distinguish between the correct stroke and the various types of wrong strokes. In the beginning of the system deployment, it was feed by ground truth templates from each type of stroke using data from 10 professional swimming athletes. An elite coach was asked to select the best strokes from each of the swimmers. We have applied cross-validation between swimmer strokes to select best 4 strokes to be used as templates for each class.

This classification is performed using fast dynamic time warping (FDTW) [3] classifier algorithm. The algorithm gives the distance cost between two different strokes. iSwimCoach calculates the cost distance between each window stroke and all templates and then classify each window stroke to the type of the template with the less cost distance.

The result data from classification process goes to the final section were these data are shown through a Web application for the coach and a vibration sensor for the swimmer.These data are shown live to the coach in a web application screen were all the swimmers data are displayed live. The coach screen shows the the time taken by each swimmer in his swim, number of strokes made, number of correct strokes, number of wrong strokes, the duration of each stroke and the classification result of each stroke with the picture of the wrong if there was a wrong stroke. The swimmer can be notified by the mistake he made on real time by a vibration sensor in his hand were a unique vibration pattern (long, short, 2 short, 2 long) is sent to him depending on the type of mistake he made.

The system has a module built for the coach as a web application; where the coach can find all the details regarding all the swimmers. The application provides the coach with reports for the swimmers. These reports include details about the training and performance of the swimmers. The coach can select a swimmer and generate its report. This would include number of overall strokes, number of laps performed, number of strokes in each lap, number of correct strokes, and number of incorrect strokes. Each incorrect stroke is classified and corrected. This helps the coach stress further on the mistakes performed by the swimmer. For example if the swimmer moves his elbow at an angle of inclination more than 45 degree, this is classified as wrong hand (elbow) entry angle. This system can be alternatively used as an e-coach as all the mistakes are classified and corrected in the reports as shown in Figure 3. The swimmer can have access to these reports which show him where are his mistakes and how he can correct them.

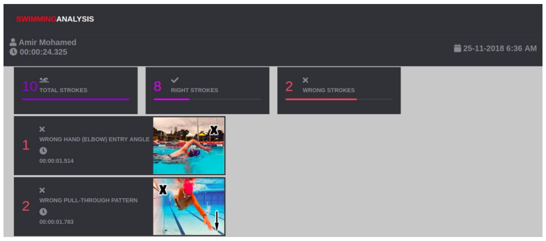

Figure 3: Report for swimmer's classified movements.

4 EXPERIMENTS

We performed three experiments, first decide which classifier that will be used for further evaluation of iSwimCoach. Second, an experiment to determine the accuracy of the selected classifier when classifying a stream of strokes in a controlled laboratory experiment. Third experiment is a practical case study that was done to determine the accuracy of the classifier when classifying a stream of freestyle strokes online. The experiment was done inside an Olympic swimming pool with a national swimming championship. The sensor being used for collecting data was an accelerometer sensor in a smartphone. The smartphone is placed in a fixed horizontal position on the swimmer's right wrist. After collecting dataset from participants we cross-validate the dataset to get the best 3 templates for each pattern made by the user. The templates data are used as a training data and the rest of the data used as testing data. Six subjects were asked to mimic a set of 6 shapes (circle, V-letter, and S-letter in clockwise and anti-clockwise). The dataset has been collected from each subject by asking them to mimic each shape by moving the smartphone in the required sequence in space. Each shape was recorded 3 times by each user; we have 18 samples for each shape. We test our dataset for the users independently. The classifiers being tested in this experiment are KNN, Naive Bayes, SVM and DTW. The collected data is then cross-validated to determine the training samples for each shape. Furthermore, we have tested the DTW among the swimmer's strokes, we have conducted a laboratory controlled experiment. Each subject has to wear the mobile device on his right hand and perform the gesture shapes for each stroke in the laboratory as if he is conducting above water training. The subjects were guided through the experiment process by instructions for doing the correct and wrong techniques. We invited five swimmers, 2 males and 3 females, to perform 4 separate streams of freestyle swimming. Two of the athletes are classified as elite swimmers and subscribed to national competitions several times. The other three athletes were considering intermediate with minimum 2 years of practicing swimming sport. Among the four streams, one is performed in the correct sequence of movements and the other 3 are incorrect. The three mistakes that are done are (wrong recovery, wrong hand entry and wrong high elbow). Each swimmer performs 10 strokes of these techniques sequentially. The results were divided into two categories user dependant and user independent. First, in user dependant test, each swimmer test results with his own training templates. Second, in user independent we test user strokes across all the other swimmers data. After that, we tested iSwimCoach in practice under the water. The setup used was the same as experiment II, the difference is that the swimmer records the strokes under the water. The stream collected from the swimmer is freestyle swimming strokes. The swimmer in this case study is an elite swimmer(a world swimming champion). We inquired him to perform 4 separate streams of freestyle swimming. Among the four streams, one is done in the correct sequence of movements and the other 3 are incorrect. Each session is done as a continuous stream that represents 50 meters of swimming that contain from 9 to 14 Stroke per each stream.

4.1 Results and Discussion

Concerning KNN, we use two different K-values k=3 and k=5 but 3 nearest neighbors gives the highest accuracy which is 55% Concerning Naive Bayes, less accuracy was obtained as 46.5%. Concerning SVM, we use the polynomial kernel with an accuracy of 60%. Accordingly, to this experiment we concluded that DTW shows the best results among the tested classifiers which is 91.5%. Therefore, iSwimCoach will be using the DTW algorithm for our further evaluations. Regarding user-dependent, the average accuracy for the five swimmers is 88% and the standard deviation is 6.08 which mean that results are close to each other. Concerning user-independent, we reported 85% accuracy. However, there is extremely confusion between wrong entry and wrong recovery because of the similarity in the pattern of the two strokes shapes. So according to experiment II result we prove that iSwimCoach by the aid of FastDTW can classify between right and wrong freestyle strokes out of the water in an acceptable manner.

Regarding the user Practical case study iSwimCoach has achieved 91% accuracy. iswimCoach system has no confusion in right stroke and wrong hand entry stroke. But it was confused two times in wrong recovery. We conducted an interview with the swimming champion, he reported that this system could be very helpful in training specially for intermediate swimmers. The main problem was in the size of the wearable mobile device, however the idea of moving this to hand wrist band could be helpful in future. We have also shown the system to two national swimming coaches, and they were very satisfied by the final generated report. They recommended seeing this system in a form of a mobile application, so they can watch each swimmer performance in the water.

5 CONCLUSION

We have proposed a swimming analysis and feedback system. We have used and developed the algorithms to extract some parameters such as the number of strokes and identify the stroke whether is it a right stroke or not. We were successfully able to achieve an acceptable accuracy using DTW algorithm between other algorithms which is 91.5%. Moreover,an accuracy of 88% when using user-dependant. Regarding user-independent, the system states accuracy 85% was achieved by DTW. In the latest practical case study, we achieved 91% accuracy. The smartphone could be replaced by a smart hand wrist band with accelerometer sensor in the future. In addition to applying deep learning algorithms on the collected data could achieve better classification accuracy and including the Augmented Reality model.

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