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Using Machine-Learning Technology to Implement a Nonhardware and Inexpensive Posture Detection System for Analyzing Body Posture Angles in Front Crawl Swimming

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Abstract. Swimming is a sport that relies heavily on motor skills. Inability to maintain adequate bodily balance in water prevents swimmers from remaining afloat and propelling themselves. Due to the difficulty of attaching reflective stickers or LED (light-emitting diode) emitters to the body while adjusting the swimming posture, it is not possible to capture the posture like during a bicycle fitting; the refraction of water also affects the detection of the body's posture. Addressing the shortcomings, this study developed a low-cost nonhardware posture detection system based on machine-learning models in MediaPipe. The system provides real-time and post analyses of posture angles and posture lines during front crawl swimming, thereby facilitating observation of the relationship between angle at which the arm enters the water and the body horizon. Two participants practicing front crawl were invited to test the proposed system. The experimental results confirmed that the proposed system provides effective detection and analyses of posture lines and angles in swimmers. The study also proposed the algorithm for optimizing posture angle detection to solve the problems of posture line distortion and angle calculation errors that arise when MediaPipe was used to detect a human skeleton above a water line. The system does not require the installation of hardware and is inexpensive to deploy, and it can be widely applied in front crawl swimming lessons to help learners adjust their arm's entry angle and body horizon to reduce forward drag and increase speed.

Keywords: machine learning, posture detecting system, body posture angles, front crawl swimming

1 Introduction

Swimming performance depends largely on motor skills. Swimmers who fail to maintain their balance in water cannot remain afloat or swim effectively. In general, nonprofessional swimmers find it challenging to identify aspects of their techniques that require improvement because they lack a professional training environment and appropriate equipment [1].

In cycling sports, each rider has a different physiological structure. To prevent riders from sustaining injuries due to incorrect riding postures over extended periods, individual adjustments for both the rider and the bike are necessary. The Industrial Technology Research Institute has assisted Giant Group in creating Taiwan's first AI high-precision bicycle fitting system. They introduced the DCF (dynamic cycling fit) system, which utilizes dual-sided 3D dynamic cameras to capture riding postures [2]. Other companies like Velogicfit [3], SHIMANO [4], and RETÜL [5] have also launched dynamic riding posture analysis systems. These systems use cameras to capture reflective stickers or LED (light-emitting diode) emitters attached to the body, enabling the identification of the torso curve for posture capture and bike fitting. This assists riders in adjusting their riding postures. However, the high cost and complexity of these systems pose significant challenges to their widespread adoption.

As indicated by the literature review, using video equipment to analyze swimming posture entails considerable costs and time spent on equipment installation. In addition, this approach cannot give swimmers real-time feedback with which they can immediately adjust their posture, and time must be spent on post analyses and video

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processing. Data obtained using video equipment are frequently affected by various types of interference, including that caused by water flow and pool surface reflection, undermining the quality of the video data. Although IMUs can be used to directly obtain sensor data, swimmers must wear such devices. When adjusting swimming posture, it's difficult to attach reflective stickers or LED emitters to the body, unlike in bike fitting where riding posture can be captured. Challenges such as water refraction also affect the detection of the body's posture. Currently, most methods rely on video equipment and IMUs (inertial measurement units) to gather data, but capturing the swimming posture curve underwater for dynamic adjustments is not yet feasible.

To address the aforementioned shortcomings, machine-learning (ML) models constructed in MediaPipe were used to replace reflective stickers and LED emitters, offering a solution to this issue. This study employed MediaPipe as the foundation of a nonhardware system for detecting swimmers' posture angles and lines during the front crawl. The system can be deployed in a swimming environment at low cost and provides real-time and post analysis functions. Both coaches and nonprofessional swimmers can use the developed system to evaluate swimming performance and obtain referential data to further improve their swimming techniques.

2 Literature Review

This study presents a review of the literature on the application of videos in swimming lessons, digital measurement sensors in swimming lessons and ML for human skeleton detection.

2.1 Application of Videos in Swimming Lessons

In practice, videos must be numerically processed and analyzed by a coach or sports scientist before they can be applied in swimming lessons [6-7]. Because data processing and analyses take considerable time, videos cannot give swimmers real-time feedback (i.e., telling them how to adjust their techniques). At least one videorecorder suitable for underwater filming is needed to capture videos of underwater sports. In addition, an underwater dolly system is required to film swimmers who are not practicing in an infinity pool. Underwater filming devices are expensive and entail complex installation procedures. Consequently, applying such devices to swimming lessons and technique analyses in a nonprofessional training setting is highly difficult [8].

In sum, using video equipment to perform post analyses has several disadvantages, including a long hardware installation time, high equipment costs, the need for a complex experimental environment, and an inability to provide real-time feedback to swimmers. Moreover, time must be taken to process video data and conduct analyses after a practice session has taken place. Interference from the flow of water, pool surface reflections, and bubbles also frequently affects the details of swimming postures captured in videos, further impeding analyses [8-11].

2.2 Application of Digital Measurement Sensors in Swimming Lessons

To resolve the aforementioned shortcomings of video analyses, scholars have used digital sensors to obtain swimming data. The advancement of digital technology has enabled the production of small sensors that can be directly worn by athletes. Such sensors can record the movement and reaction of swimmers, providing an alternative to video analyses. Wearable digital sensors including accelerometers, gyroscopes, and magnetometers are generally called IMUs. A single IMU might comprise a single sensor or multiple sensors. IMUs have become a popular tool for analyses of posture during swimming [12-16] because their use is not limited to experimental sites; they can be worn in natural swimming environments, acquiring more swimming data than can be obtained when being tested in environments with limited experimental conditions [17].

2.3 Application of ML for Human Skeleton Detection

Developed by Google Research, MediaPipe is a multimedia framework that provides a suite of ML tools. It is mainly used to create multimode (e.g., video, audio, or time sequence data) applications that run in multiple operating environments (e.g., on personal computers, Android, and iOS devices). MediaPipe can be used to convert sensor data into modular diagrams through methods including model inference, media processing algorithms, and data transformations. It is also commonly used by professional ML practitioners. MediaPipe provides numerous detection functions including full-body detection, palm tracking, facial tracking, posture detection, face mesh detection, and object detection [18]; hence, it has been widely applied in various fields [19-24]. The present study used MediaPipe Pose to detect the posture of swimmers.

2.4 Summary

This study discusses the results of a literature review, as shown in Table 1. According to the purpose of this research, the aim is to replace the use of reflective stickers and LED emitters for detecting body posture and to build a testing environment at a lower cost. This environment will provide real-time and post-analysis to coaches or swimmers as a reference for improving front crawl swimming practice.

Based on Table 1, it can be observed that the front crawl swimming posture detection system built using MediaPipe requires less hardware installation time, has lower testing environment costs, and is easy to set up in an experimental environment. With this system, the body posture can be detected without wearing sensors. Furthermore, it offers both real-time and post-analysis capabilities. Indeed, this appears to be the most suitable solution for this study.

Table 1. Comparison of related works

Item	Videos	Digital Measurement Sensors	MediaPipe
Hardware installation	Long	Medium	Less
Equipment costs	High	Medium	Low
Experimental environment	Complexity	Normal	Simple
Real-time feedback	No	Yes	Yes
Post analysis	Yes	Yes	Yes
Posture detection	No	No	Yes
Wear sensors	No	Yes	No

3 Introduction to System Features and the Proposed Algorithm

Considering that the angle at which a swimmer's arm enters the water impacts their overall body alignment while performing the front crawl, this study devised the proposed system with a specific focus on analyzing the arm entry angle and body alignment. In this section, the system design, posture angle detection, customization of posture lines, exporting of posture angle data, and the algorithm aimed at optimizing posture angle detection are presented.

3.1 System Design

Fig. 1 presents the architecture of the proposed system, which comprises three major components, namely posture angle detection, posture line reconstruction, and posture angle data export. The three components are detailed as follows.

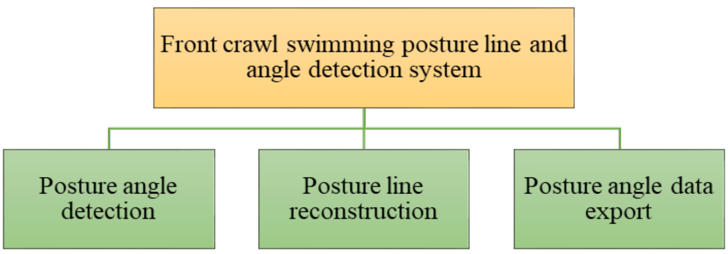

Fig. 1. System structure

The proposed system was developed using Python in combination with several development tools, namely Visual Studio Code, Open Source Computer Vision Library, and MediaPipe Pose, a pose detection model in MediaPipe.

The system environment comprised one computer and camera as the hardware (Fig. 2) and Python and Visual Studio Code as the software (Fig. 3). The system deployment cost was low because the installation of additional software was not required and the software programs that were adopted were free.

Fig. 2. Required hardware

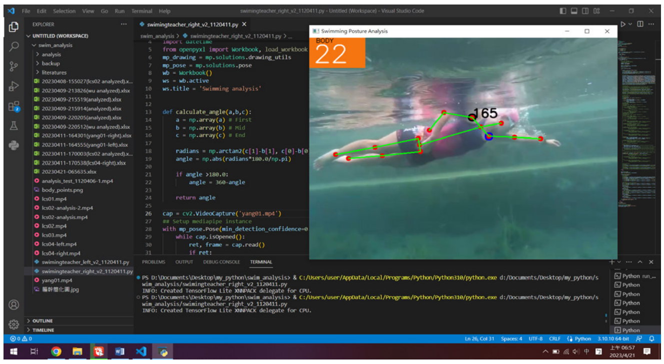

Fig. 3. Required software

Fig. 4 presents the design of the system's interface. The interface provides data on joint angles, posture angles, and posture lines to facilitate swimming analyses.

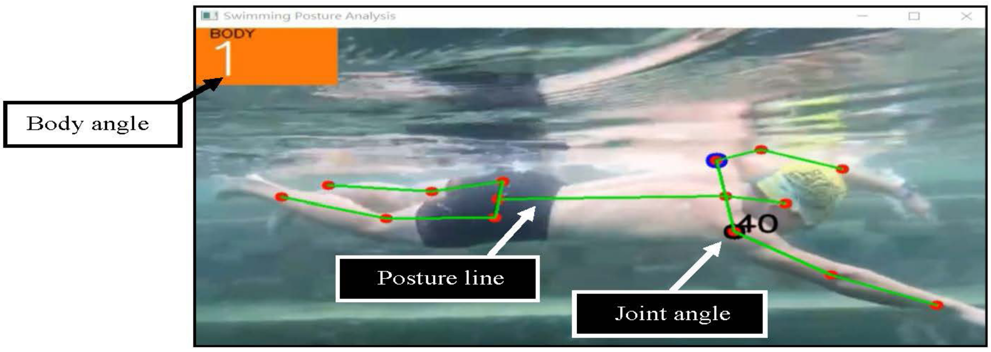

Fig. 4. Interface design

3.2 Posture Angle Detection

The proposed system enables real-time detection and video analyses. When cameras are used to directly film swimmers in pools, the system detects their joint angles and posture lines from the profile view. Video recordings are also stored in the system for post analyses.

The proposed system uses the BlazePose model [25] in MediaPipe Pose to estimate the center point of the hips, the circumscribed circle radius of the entire body, and the angle of inclination that the intersection of the line connecting the shoulder and hip center points forms with the x-axis; in total, the positions of 33 pose landmarks are detected (Fig. 5).

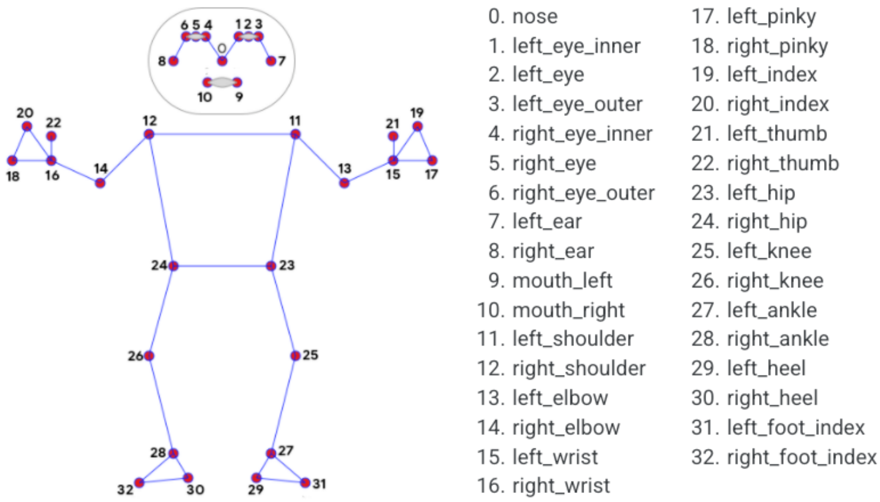

Fig. 5. Landmark model of MediaPipe Pose [26]

Once the landmarks have been detected, each joint angle is calculated. One joint angle is formed by three landmarks. The calculation is conducted as follows. First, three points are identified in the system's coordinates, namely *a(x,y)*, *b(x,y)*, and *c(x,y)*, as illustrated in Fig. 6. The middle point is *b(x,y)*, and the three points form an angle at *b(x,y)*. Equation (1) is used to determine the angle. The overall calculation process is performed using the following algorithm:

```
def calculate_angle(a,b,c):
     a = np.array(a); #First point
     b = np.array(b); #Middle point
     c = np.array(c); #End point
     radians = np.arctan2(c[1]-b[1], c[0]-b[0]) - np.arctan2(a[1]-b[1],
     a[0]-b[0]);
     angle = np.abs(radians*180.0/np.pi);
     if angle >180.0:
     angle = 360-angle;
     return angle
```

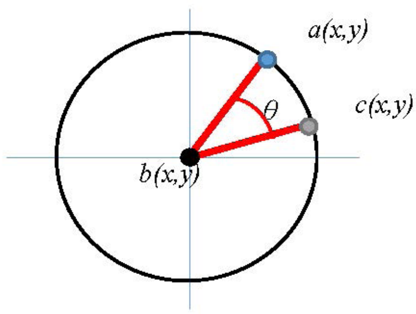

Fig. 6. Coordinates of points *a*, *b*, and *c*

$$\theta_n = \left|\left(\operatorname{atan2}\left(c_{n(y)} - b_{n(y)}, c_{n(x)} - b_{n(x)}\right) - \operatorname{atan2}\left(a_{n(y)} - b_{n(y)}, a_{n(x)} - b_{n(x)}\right)\right) \times \frac{180}{\pi}\right|. \tag{1}$$

3.3 Construction of Customized Posture Lines

In the proposed system, MediaPipe Pose generates the posture lines between all landmarks. However, the resulting model can appear overly complex because some joints and body lines are not relevant to posture detection. Therefore, the posture line model is customized in accordance with the posture angles to be examined in swimming analyses. Fig. 7 presents the set of customized posture lines.

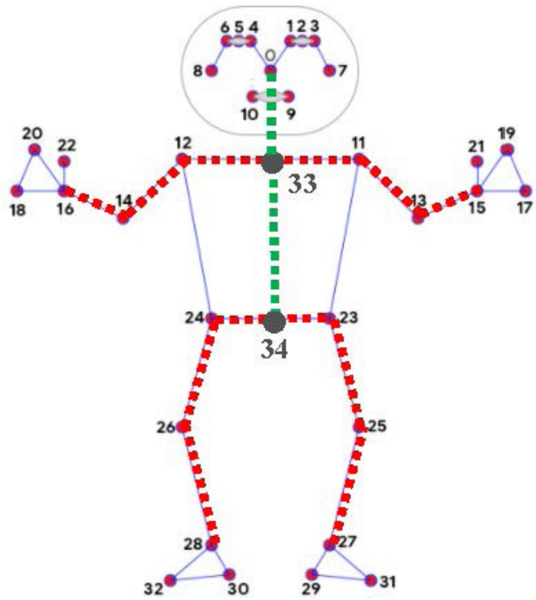

Fig. 7. Set of customized posture lines

Once the locations of points 33 and 34 have been determined, points 33 and 0 are connected to create a new posture line, and points 33 and 34 are connected to create another posture line. This process is performed through the following algorithm. Fig. 8 presents the result of posture line customization.

```
#line of nose and shoulder center points
img = cv2.line(image,
    (int(landmarks[0].x*imgWidth),int(landmarks[0].y*imgHeight)),
    (int(Landmark33[0]*imgWidth),int(Landmark33[1]*imgHeight)),
    (0,255,0), 2);
#line of shoulder center and hip center points
img = cv2.line(image,
    (int(Landmark33[0]*imgWidth),int(Landmark33[1]*imgHeight)),
    (int(Landmark34[0]*imgWidth),int(Landmark34[1]*imgHeight)),
    (0,255,0), 2);
```

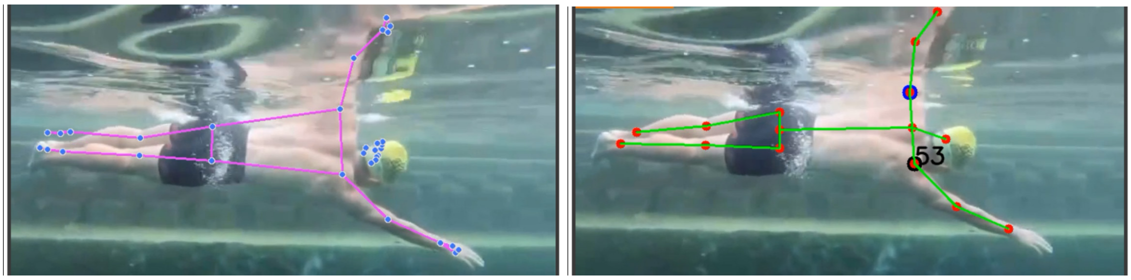

Fig. 8. Comparison of the original (left) and customized (right) line models

3.4 Posture Angle Output

Because the body horizon of a swimmer is affected by the angle at which their arm enters the water, the proposed system focuses on detection of the forearm entry angle and the angle formed by the body and horizontal axis. The detected angle data are exported as Excel files, and line graphs are generated for further analyses.

The angle calculation was introduced in Section 2.2. Assuming that the subject is viewed from their right side, the coordinates of the right elbow, right shoulder, and right horizontal level are needed to calculate the angle between the right forearm and right horizontal level by using Equation (1). The aforementioned three sets of coordinates are obtained using the following algorithm:

```
#Get coordinates
right_elbow = [landmarks[mp_pose.PoseLandmark.RIGHT_ELBOW.value].
   x,landmarks[mp_pose.PoseLandmark.RIGHT_ELBOW.value].y];
right_shoulder = [landmarks[mp_pose.PoseLandmark.RIGHT_SHOULDER.value].
   x,landmarks[mp_pose.PoseLandmark.RIGHT_SHOULDER.value].y];
right_hori_level=[50+landmarks[mp_pose.PoseLandmark.RIGHT_SHOULDER.val-
   ue].x,landmarks[mp_pose.PoseLandmark.RIGHT_SHOULDER.value].y];
```

To calculate the angle between the body and horizontal level, the coordinates of the hip center point, shoulder center point, and body horizontal level are needed. The three sets of coordinates are obtained using the following algorithm:

```
#Get coordinates
a = np.array([[landmarks[23].x,landmarks[24].x], [landmarks[23].y,land-
   marks[24].y]]);
hip_center_point=np.mean(a,axis=1); #hip center point
b = np.array([[landmarks[11].x,landmarks[12].x], [landmarks[11].y,land-
   marks[12].y]]);
shoulder_center_point=np.mean(b,axis=1); #shoulder center point
body_hori_level=[-50+shoulder_center_point[0],shoulder_center_
   point[1]];
```

The calculated angles are then exported as Excel files by using the following algorithm. The data are employed for generating analysis graphs.

```
ws.append([‘BODY’, (body_angle),’RIGHT_SHOULDER’, (right_shoulder_val-
   ue)]);
```

3.5 Algorithm for Optimizing Posture Angle Detection

The results revealed problems that could not be overcome by MediaPipe alone for the detection of a human skeleton. Specifically, when the system failed to detect the human body, skeleton lines would be lost and corresponding posture lines generated would be erroneous. For example, Fig. 9 depicts detection errors that occurred when part of the human body was above the water. This happened when one arm left the water before re-entry, causing the arm to disappear from the camera's view. This impeded the detection of posture lines, and the calculation of the arm entry angle was thus incorrect.

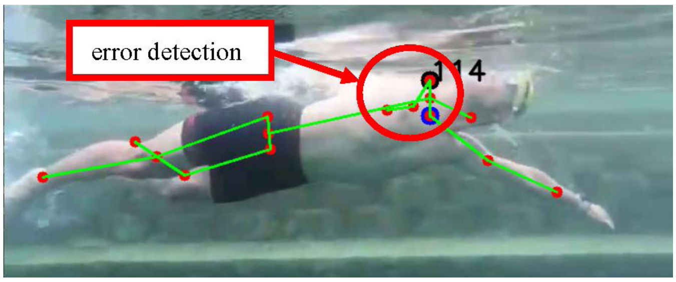

Fig. 9. Distortion of posture lines in the arm

In response to this problem, the following algorithm was proposed to optimize the data analysis process. In the proposed approach, only data obtained underwater are exported. When an above-water datum is detected, it is omitted, and the underwater datum beforehand is exported instead. Actual testing revealed that the optimal results were obtained when the left and right shoulder landmarks were used as the basis of interpretation.

```
if (right_shoulder[1] > left_shoulder[1]): #allow the angle with elbow
   below the shoulder
   right_shoulder_value = right_shoulder_angle;
   right_shoulder_prevalue_tmp= right_shoulder_angle; #store the
   pre-value of right shoulder angle
else:
   right_shoulder_value = right_shoulder_prevalue_tmp; #use pre-value
   angle to avoid the error data
ws.append([‘BODY’, (body_angle),’RIGHT_SHOULDER’, (right_shoulder_val-
   ue)]);
```

4 Experimental Design and Analysis

This section introduces the experimental design and experimental analysis. It discusses the results of applying the proposed optimization algorithm and compares the swimming performance of the participants to verify that the system's functionality meets the research's objectives.

4.1 Experimental Design

Two participants practicing front crawl were invited to test the proposed system. Participant A had been practicing front crawl swimming for 1 year (breathing in on the left side), whereas Participant B had been practicing front crawl swimming for 3 years (breathing in on the right side). A camera was used to film the participants from the right side, and the recordings were used for post analyses. The results of the proposed algorithms and optimization methods, analysis graphs, and comparison with other methods are detailed as follows.

4.2 Experimental Analysis

Results of Applying the Proposed Optimization Algorithm. A post analysis was performed on the video recordings of the two participants. Fig. 10 presents the original analysis graph of Participant A. The red line represents the right arm's angle of entry, whereas the blue line represents the body horizon angle. The results revealed that the line segments shown in Fig. 10 fluctuated considerably, as if the results were being affected by noise. These fluctuations occurred when the camera could not capture the right arm while it was above water, resulting in distortion of the detected posture lines.

Fig. 11 presents the optimized analysis graph. The proposed optimization method successfully smoothed the line segments and highlighted the patterns of interest. This would enable a user to effectively interpret the collected data and understand the relationship between the arm's entry angle and body horizon.

Fig. 12 and Fig. 13 present the original and optimized analysis graphs, respectively, for Participant B. The strongly fluctuating line segments in Fig. 12 are again smooth in Fig. 13, enabling effective analyses and interpretation. This finding confirmed the effectiveness of the proposed optimization method.

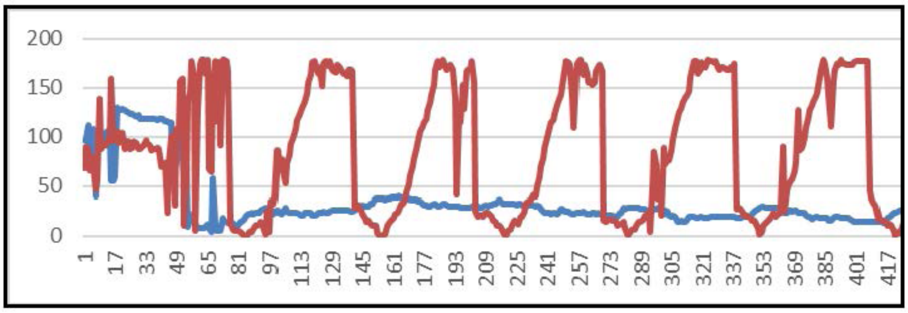

Fig. 10. Original analysis graph for Participant A

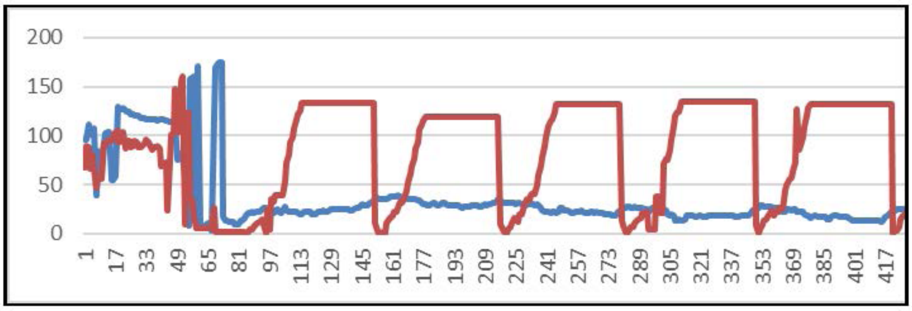

Fig. 11. Optimized analysis graph for Participant A

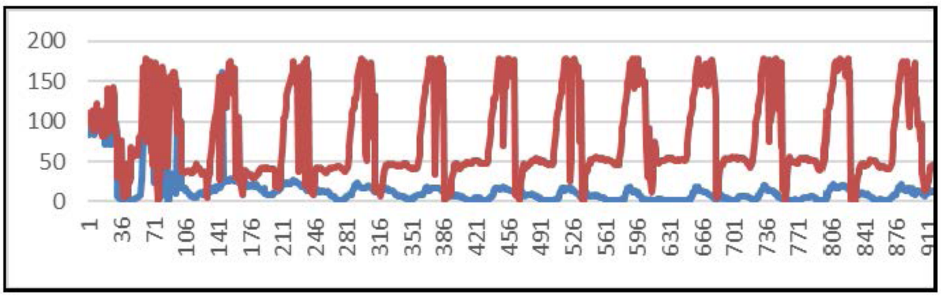

Fig. 12. Original analysis graph for Participant B

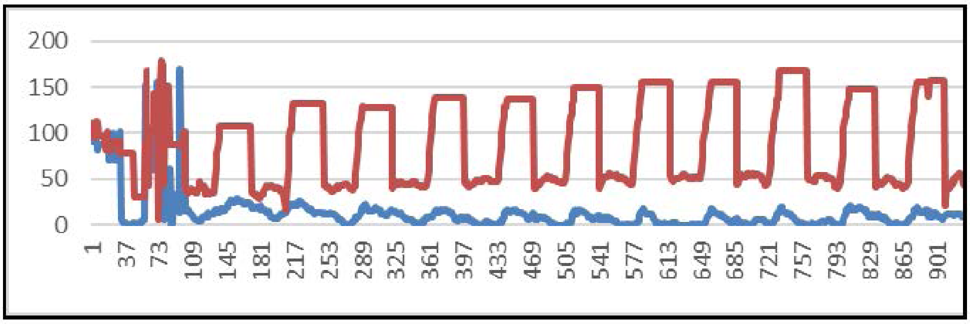

Fig. 13. Optimized analysis graph for Participant B

Comparison of the Swimming Performance for Participants. One line segment was extracted from each of the analysis graphs for Participants A and B, and the information reflected by the line segments was interpreted. Fig. 14 and Fig. 15 present the extracted line segments for Participants A and B, respectively. Videos were captured from the right side. The red and blue lines represent the right arm's angle of entry and body horizon angle, respectively. By examining the graphs, a user can observe the right-hand anchoring process, the maximum and minimum angles between the body and water horizon (which indicates the level of sinking), and the body horizon of the swimmer while they are breathing.

The extracted line segments for Participant A revealed large fluctuations in the right-hand anchoring process, indicating that the hand was not anchored at a fixed position. The maximum and minimum angles between the body and water horizon were 40° and 25°, respectively. The average angle is 32.5°. The swimmer sank slightly when breathing in on the left side.

The line segments for Participant B revealed a more stable right-hand anchoring position. The maximum and minimum angles between the body and water horizon were 20° and 0°, respectively. The average angle is 10°. This swimmer also sank slightly when breathing in on the right side.

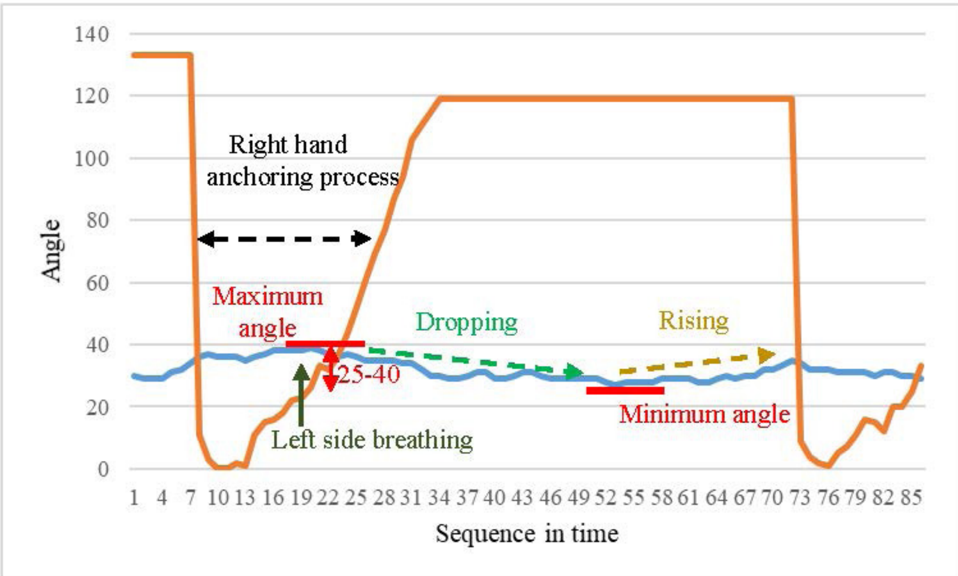

Fig. 14. Extracted line segments for Participant A

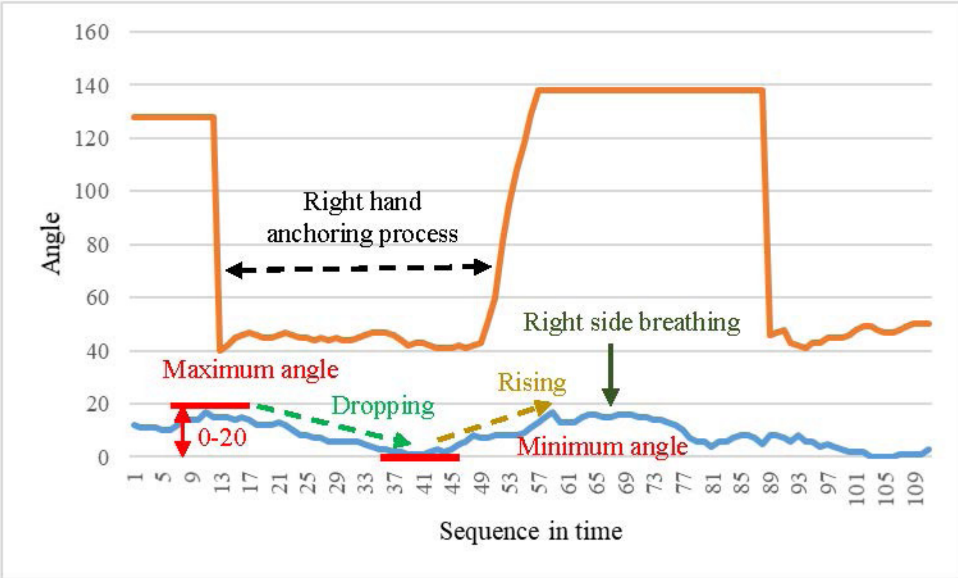

Fig. 15. Extracted line segments for Participant B

Comparing the analysis results of the two participants (as shown in Table 2) revealed that Participant A was more able to maintain their right hand at a specific angle during the anchoring process, thereby sustaining their angle between their body and the water horizon. Larger maximum and minimum angles were observed between the body of Participant A and the water horizon, indicating a higher level of sinking and greater forward drag for this participant than for Participant B. Both participants sank slightly while breathing in, indicating larger forward drag during this phase.

Table 2. Comparison of Participants A and B

Item	Participant A	Participant B
The maximum angle between the body and water horizon	40°	20°
The minimum angle between the body and water horizon	25°	0°
Body resistance	Greater resistance	Less resistance
The sinking condition during breathing	Slightly	Slightly

4.3 Summary

Comparison with the findings of relevant literature reveals several strengths of the proposed system. Specifically, the system does not require the installation of hardware and is inexpensive to deploy. Swimmers who use the system do not need to wear digital sensors to collect data, and the system exports all data as an Excel file, enabling the generation of line graphs. Analysis graphs produced in this manner enable users to quantify their swimming performance. In addition, users can capture swimming films on their own first and then upload the films to the system for post analyses.

5 Conclusion and Future Work

Swimming performance is largely dependent on athletic skills. Swimmers who cannot maintain balance in the water struggle to stay afloat or swim effectively. Due to the challenges of attaching reflective stickers or LED emitters to the body while adjusting swimming posture, capturing posture like in bike fitting is not feasible. Additionally, issues such as water refraction affect the detection of the body's alignment. Currently, video equipment and IMUs are predominantly used to gather data, but capturing the dynamic swimming posture curve underwater remains a challenge. This study addressed the shortcomings by developing a low-cost nonhardware posture angle and line detection system based on ML technology in MediaPipe. The system replaces reflective stickers and LED emitters and provides real-time and post analyses, enabling users to observe the relationship between the angle at which their arm enters the water and their body horizon during front crawl.

The study proposed the algorithm for optimizing posture angle detection to solve the problems of posture line distortion and angle calculation errors that arise when MediaPipe was used to detect a human skeleton above a water line. The proposed optimization method also smooths the line segments in analysis graphs to accentuate patterns of interest and thus facilitates clear interpretation of collected data. Two participants practicing front crawl were invited to test the proposed system. The experimental results confirmed that the proposed system provides effective detection and analyses of posture lines and angles in swimmers.

The system does not require the installation of hardware and is inexpensive to deploy. Swimmers who use the system do not need to wear digital sensors to collect data, and the system exports all data as an Excel file, enabling the generation of line graphs. Analysis graphs produced in this manner enable users to quantify their swimming performance. In addition, users can capture swimming films on their own first and then upload the films to the system for post analyses. It can be applied in front crawl swimming lessons to help learners adjust their arm's entry angle and body horizon to reduce forward drag and increase speed. The current system only provides real-time feedback on the angle at which the arm enters the water and the body's horizontal position. Further development can focus on real-time feedback, providing instant reminders to the swimmer about areas that need improvement, eliminating the need for interpretation by a coach or the swimmer.

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