

OpenPose Technology Based Yoga Exercise Guidance Functions by Hint Messages and Scores Evaluation for Dynamic and Static Yoga Postures

Wan-Chia Huang¹, Cheng-Liang Shih¹, Irin Tri Anggraini², Nobuo Funabiki², and Chih-Peng Fan^{1,*}

¹Department of Electrical Engineering, National Chung Hsing University, Taichung, Taiwan;
Email: a0908652289@gmail.com (W.-C.H.), as5577557@gmail.com (C.-L.S.)

²Department of Electrical and Communication Engineering, Okayama University, Okayama, Japan;
Email: pq7n2xt6@s.okayama-u.ac.jp (I. T.A.), funabiki@okayama-u.ac.jp (N.F.)

*Correspondence: cpfan@dragon.nchu.edu.tw (C.-P.F.)

Abstract—In this study, the proposed system provides the hint message and hint music functions to guide users through Yoga exercise movements, and the proposed score calculation method is used not only for evaluating and comparing the similarity between the instructor and the user in the static movement, but also for observing the performance of the user in dynamic postures. In yoga exercises, in addition to focusing on maintaining static poses, the changes of dynamic movements between static poses are also very important. In this paper, the conditions of how to implement the hint functions and how to design two score calculations for evaluating static and dynamic postures are introduced. Finally, for various Yoga exercises, the experimental results show that by using the difference of the shape distributions at the static poses mode, and by using the new score distributions combining with static poses and dynamic motions, the proposed guidance and hint functions provided for the self-practice Yoga exercise system are worked effectively.

Keywords—Yoga exercise, OpenPose, duration time, net resolution, dynamic region, static region, hint function, hint message, hint music, shape_score, final score

I. INTRODUCTION

In recent years, due to the COVID-19 issue, it makes people stay at home more frequently and has less contact with outdoor activities, lets activities at home become very important, and yoga is a suitable exercise can be done at home. The “BODY25” model of OpenPose [1, 2] is applied in the proposed system to extract skeleton information, a person or multiple people through the “BODY25” model, the body skeleton and 25 key-points coordinates are extracted. Because of this, the proposed system uses the “BODY25” model to apply on the instructor’s videos and user’s images to get their key-point information, the instructor and user images after processing by “BODY25” model are shown in Fig. 1. Anggraini *et al.* [3] provided five Yoga exercises,

including “Mountain”, “Seat_1”, “Seat_2”, “Side_bend” and “Warrior”, respectively for this system.

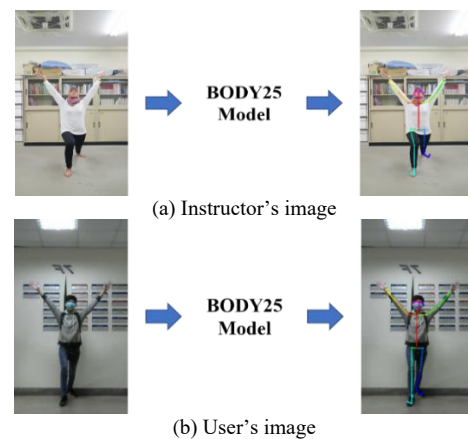


Figure 1. Examples of images after processing by the “BODY25” model.

Shen *et al.* [4] proposed the fuzzy-based scoring system and calculation methods of the total distance in the instructor’s video and angle difference between instructor and user. The score obtained from fuzzy-based scoring system more emphasized on the posture similarity. Shen *et al.* [5] integrated the back-end algorithm with front-end UI interface for user interactions on Nvidia Jetson Nano. For the guiding functions, the arrow guidance is provided to help users perform movements. However, in terms of function development and score calculation, the system aims to add more functions to provide users with a wider range of choices based on their needs and diverse score calculations on score presentation. Because of this, the proposed system provides different functions for scoring and guidance this time, in order to add more features to help users on the guidance of the poses, the hint message function and hint music function are provided for users to give the hints on poses and guide the user with text messages, music and sound. Besides, more considerations are added into the original scoring system, by distinguishing two different types of regions in yoga

exercises to give different score types and increase the diversity of scores, presents more features on scores.

II. RELATED WORKS

Hirasawa *et al.* [6] applied the key-points detect on home squat training. Qiao *et al.* [7] presented a real-time 2D human gesture grading system on Tai Chi movements. Li *et al.* [8] proposed a system to estimate the swing performance of the basketball hitter. Park *et al.* [9] proposed a real-time image-based classifier to count push-ups. Jafarzadeh *et al.* [10] presented a 2D real-time athlete estimation system using OpenPose. Abe *et al.* [11] developed a Parkinson’s Disease diagnosis system using the bilateral differences between left and right arm swings with OpenPose. Shen *et al.* [12] implemented the total distance to classify three specific types of frames in the instructor video, initial frame, keyframes and sync frames.

III. STATIC AND DYNAMIC YOGA REGIONS

There are many dynamic regions and static regions in a Yoga exercise. If the interval is from an initial frame or a sync frame to a keyframe in an instructor’s video, the interval is identified as a dynamic region. This is because an initial frame or a sync frame stands for the moment when the static pose starts to move, and the keyframe stands for the frame is a static pose. The motions in a dynamic region are a series of non-stop actions until the end of the pose.

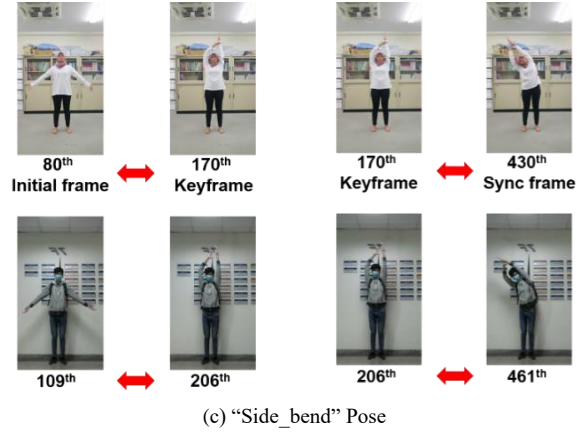
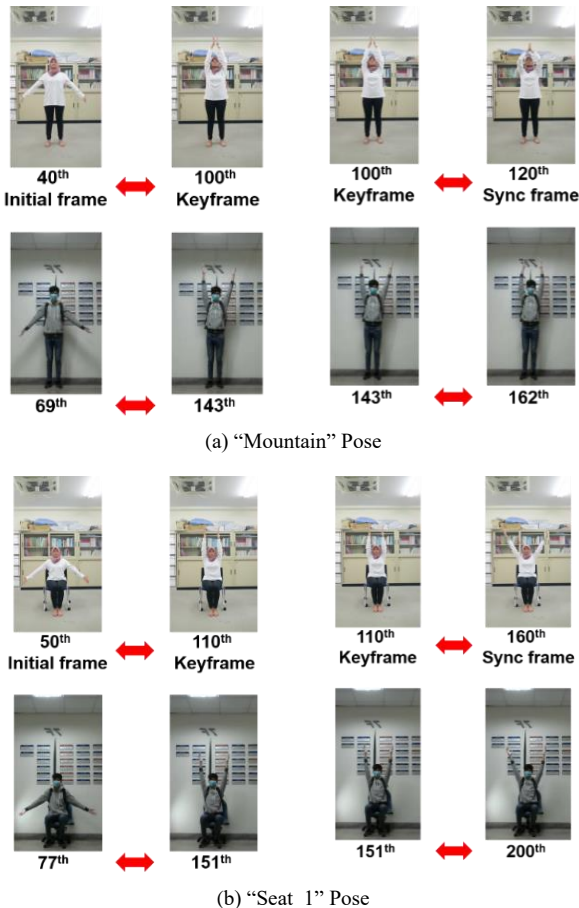


Figure 2. Schematic of dynamic and static regions in different poses.

The static region is the opposite of the dynamic region, and it is an interval from a keyframe to a sync frame in an instructor’s video. The motions in a static region are a series of near-static poses until switching poses. After defining the dynamic regions and static regions, the system applies different score calculations in these regions. The schematic diagrams of static regions and dynamic regions in different Yoga exercises, including “Mountain”, “Seat_1” and “Side_bend” poses of the instructor and user as shown in Fig. 2, respectively. Besides, the corresponding static region and dynamic region of user can also be found.

In Fig. 2, the left side shows dynamic regions, and the right side reveals static regions in each pose.

IV. PROPOSED SYSTEM

A. The Duration Time of the Instructor and User

The duration time in the proposed system means the length of time between two poses, in order to find the duration of a pose in each dynamic region and static region, by subtracting the index of the keyframe from the index of initial frame or the index of the sync frame in dynamic region and subtracting the index of sync frame from keyframe in static region, the duration time of the instructor in each dynamic region and static region can be obtained, which is called DT_{ins} . The duration time calculation of user is similar as the way of instructor, by subtracting the index of key matching frame from the index of initial matching frame or the index of the sync matching frame in dynamic region and subtracting the index of sync matching frame from key matching frame in static region, the duration time of the user can be obtained, which is called DT_{user} . The DT_{ins} values in Fig. 2 from top to bottom are 60, 60, 90 at the left side in dynamic region and 20, 50, 260 at the right side in static region, and the DT_{user} values are 74, 74, 97 at the left side in dynamic region and 19, 49, 255 at the right side in static region, their units are calculated in frames.

B. Standard Duration Time and Thresholds

By using different net resolutions of the instructor videos, the overall values $\mu_{D1}, \mu_{D2}, \mu_{D3}, \dots, \mu_{DN}, \mu_{S1}, \mu_{S2}, \mu_{S3}, \dots,$ and μ_{SN} and standard deviation values $\sigma_{D1}, \sigma_{D2}, \sigma_{D3}, \dots, \sigma_{DN}, \sigma_{S1}, \sigma_{S2}, \sigma_{S3}, \dots,$ and σ_{SN} of duration times

in each dynamic region, $D_1, D_2, D_3, \dots,$ and D_N and static region $S_1, S_2, S_3, \dots,$ and S_N respectively can be obtained. After obtaining these overall and standard deviation values, then applying these values as standard duration time and thresholds in the following applications by Gaussian distributions for each dynamic region and static region. The details are shown in Table I for duration time in dynamic region, and in Table II about duration time for static region, the net resolutions for R_1 to R_7 are $-1 \times 368, 96 \times 192, 128 \times 256, 144 \times 288, 160 \times 320, 272 \times 544,$ and $352 \times 704,$ respectively.

TABLE I. DURATION TIME DISTRIBUTION IN DYNAMIC REGION

	D_1	D_2	...	D_N
R1	DT_{ins1}^{R1}	DT_{ins2}^{R1}	...	DT_{insN}^{R1}
R2	DT_{ins1}^{R2}	DT_{ins2}^{R2}	...	DT_{insN}^{R2}
R3	DT_{ins1}^{R3}	DT_{ins2}^{R3}	...	DT_{insN}^{R3}
R4	DT_{ins1}^{R4}	DT_{ins2}^{R4}	...	DT_{insN}^{R4}
R5	DT_{ins1}^{R5}	DT_{ins2}^{R5}	...	DT_{insN}^{R5}
R6	DT_{ins1}^{R6}	DT_{ins2}^{R6}	...	DT_{insN}^{R6}
R7	DT_{ins1}^{R7}	DT_{ins2}^{R7}	...	DT_{insN}^{R7}
Overall	μ_{D1}	μ_{D2}	...	μ_{DN}
Std	σ_{D1}	σ_{D2}	...	σ_{DN}

TABLE II. DURATION TIME DISTRIBUTION IN STATIC REGION

	S_1	S_2	...	S_N
R1	DT_{ins1}^{R1}	DT_{ins2}^{R1}	...	DT_{insN}^{R1}
R2	DT_{ins1}^{R2}	DT_{ins2}^{R2}	...	DT_{insN}^{R2}
R3	DT_{ins1}^{R3}	DT_{ins2}^{R3}	...	DT_{insN}^{R3}
R4	DT_{ins1}^{R4}	DT_{ins2}^{R4}	...	DT_{insN}^{R4}
R5	DT_{ins1}^{R5}	DT_{ins2}^{R5}	...	DT_{insN}^{R5}
R6	DT_{ins1}^{R6}	DT_{ins2}^{R6}	...	DT_{insN}^{R6}
R7	DT_{ins1}^{R7}	DT_{ins2}^{R7}	...	DT_{insN}^{R7}
Overall	μ_{S1}	μ_{S2}	...	μ_{SN}
Std	σ_{S1}	σ_{S2}	...	σ_{SN}

C. Hint Function by Message

In Tables I and II, the μ_D, σ_D for each dynamic region and μ_S, σ_S for each static region of the Yoga exercise are defined. The system applies two conditions to give corresponding hint messages for user suggestions. In the dynamic region, the conditions are shown in Table III, and in the static region, the conditions are shown in Table IV. Then the messages help the user to practice the Yoga exercises. The two conditions for dynamic regions are that if the user’s movement is too fast or too slow, and the two conditions for static regions are that if the posture user kept too short or too long. Fig. 3 shows the hint message examples.

TABLE III. HINT MESSAGES IN EACH DYNAMIC REGION

Conditions	Hint Messages
$DT_{user,i} < \mu_{Di} - 2 \times \sigma_{Di}$	Note users that they did the pose too fast
$\mu_{Di} + 2 \times \sigma_{Di} < DT_{user,i}$	Note users that they did the pose too slow

TABLE IV. HINT MESSAGES IN EACH STATIC REGION

Conditions	Hint messages
$DT_{user,i} < \mu_{Si} - 2 \times \sigma_{Si}$	Note users that they kept the pose too short
$\mu_{Si} + 2 \times \sigma_{Si} < DT_{user,i}$	Note users that they kept the pose too long

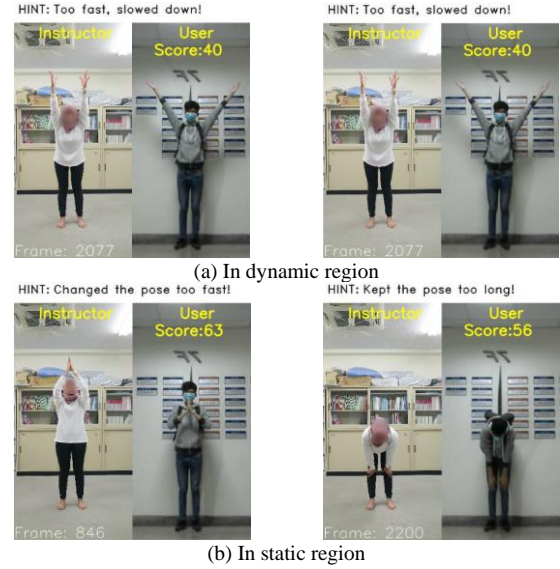


Figure 3. Examples of hint message function in each dynamic region and static region.

D. Hint Function by Music

The system collects user’s delay from initial matching frame or sync matching frames. If there are three delays, the system computes the slope and variance of the three delays, then applying the hint music function. After the function finishes, then clearing the delay and re-collecting three delays until the end of the Yoga exercise, the two conditions of hint music function are shown in Table V. First condition is if the slope is larger than 0 and variance is larger than 40, it defines as user’s moving speed becomes slower over time, the system will play the slight music to suggest the users their path should be speeded up, and second condition is if the slope is less than 0 and variance is larger than 40, it defines as user’s moving speed becomes faster over time, and the system plays the slow music to suggest users their path should be slowed down. In addition, by applying multi-threading as shown in Fig. 4, it is possible for the system to process the instructor’s and user’s frame in real-time and play the hint music in the background at the same time.

TABLE V. HINT MUSIC FUNCTION

Conditions	Actions
$m_{delay} > 0 \text{ and } Var(delay) > 40$	Play slight music
$m_{delay} < 0 \text{ and } Var(delay) > 40$	Play slow music

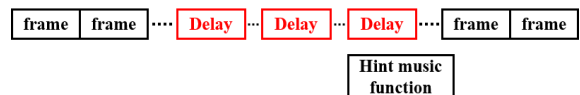


Figure 4. Multi-threading image processing for hint music function.

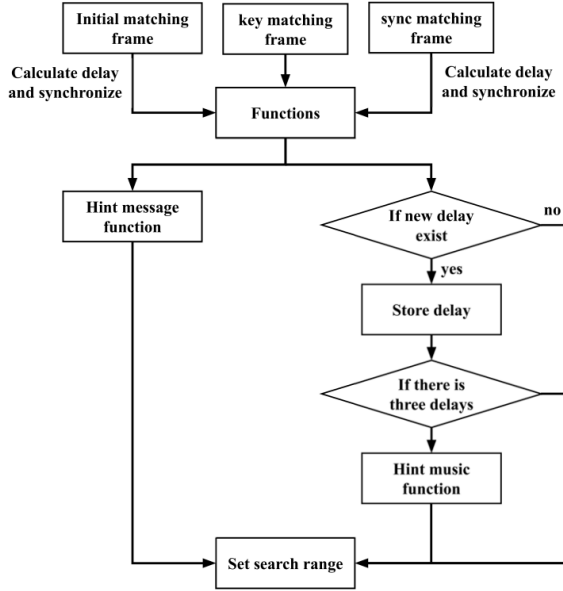


Figure 5. Design flow of the hint functions.

In Fig. 5, it shows the whole design flow of the hint function, after finding the user’s matching frame, it executes the hint message and hint music functions, determines whether the conditions are met, and finally sets the next search range until the exercise ends.

E. Calculation of “Shape_Score”

In Shen *et al.* [4], the system sets the key-point at the 2nd and 5th locations as the center points, calculates the angle corresponding to the selected key-points at the 3rd, 4th, 6th, and 7th locations of the upper body, and uses key-point at the 9th and 12th locations to calculate the angle corresponding to the selected key-points at the 10th, 11th, 13th, and 14th locations of the lower body. There are two angle difference values between instructor and user classified into left-side body and right-side body in each frame, the angle difference values are converted into a score through the fuzzy based scoring system after defuzzification. The score is defined as “shape_score” for identifying the shape similarity of the pose as five states, Bad_{low}, Good_{low}, Perfect, Bad_{high}, and Good_{high} respectively.

F. Calculation of S_{score}

The score is called S_{score} if the score is calculated in the static region. The S_{score} calculation puts more emphasis on the duration time the user maintains the poses compare to the instructor’s duration time in the static time regions. The duration time ratio formula is:

$$DT_r = \begin{cases} DT_{ins}/DT_{user}, & DT_{user} > DT_{ins} \\ DT_{user}/DT_{ins}, & DT_{user} \leq DT_{ins} \end{cases} \quad (1)$$

In Eq. (1), to prevent the ratio from being greater than one, there are two conditions to avoid it. DT_r is the ratio of instructor’s duration time and user’s duration time, DT_{ins} is instructor’s duration time and DT_{user} is user’s duration time.

After defining the ratio of the duration time between instructor and user, applying the S_{score} calculation, the formula is as:

$$S_{score} = shape_score \times \sqrt{DT_r} \quad (2)$$

In Eq. (2), S_{score} is equal to shape_score multiplied by the square root of the duration time ratio value, where the square root is to prevent the shape_score from dropping too quickly.

G. Calculation of D_{score}

The system evaluates the user’s performance in the dynamic region and gives different scores called dynamic response score DR_{score} in some conditions, DR_{score} evaluates the user’s performance for how to response on duration time after seeing an instructor’s action, the DR_{score} is defined as:

$$DR_{score} = \begin{cases} 100, & \mu_{Di} - \sigma_{Di} \leq DT_{user,i} \leq \mu_{Di} + \sigma_{Di} \\ 70, & \mu_{Di} + \sigma_{Di} < DT_{user,i} \leq \mu_{Di} + 2 \times \sigma_{Di} \\ & \mu_{Di} - 2 \times \sigma_{Di} \leq DT_{user,i} < \mu_{Di} - \sigma_{Di} \\ 40, & \text{Others} \end{cases} \quad (3)$$

In Eq. (3), if the DR_{score} is equal to 100, it means user did the pose in a proper time, 70 means the user might do the pose too slow or too fast, 40 means the user did the pose in an abnormal situation.

The score is called D_{score} if the score is calculated in the dynamic region. After obtaining the DR_{score}, the system calculates the D_{score} with a weight 0.5 for shape_score and another weight 0.5 for DR_{score}. The D_{score} formula is defined as:

$$D_{score} = 0.5 \times shape_score + 0.5 \times DR_{score} \quad (4)$$

In Eq. (4), by giving the same weights to “shape_score” and “DR_{score}” mean that in addition to paying attention to the similarity of the posture, the user should also pay attention to the mastery of timing on movement in the dynamic region.

H. Calculation of Final Score

After calculating the S_{score} and D_{score} of each region in the Yoga exercises, the system averages all S_{score} to get μ_{S_{score}} and averages all D_{score} to get μ_{D_{score}}, the formula of final score calculation is described as follows:

$$Final\ score = W1 \times \mu_{S_{score}} + W2 \times \mu_{D_{score}} \quad (5)$$

In Eq. (5), according to the proportion of time in the two regions, the system sets the W1 for μ_{S_{score}} and W2 for μ_{D_{score}} to calculate the final score for evaluating the overall performance of the user. The weightings of W1 and W2 are shown in Table VI.

TABLE VI. WEIGHTS W1 AND W2

	W1	W2
Mountain	0.25	0.75
Seat_1	0.55	0.45
Seat_2	0.5	0.5
Side_bend	0.7	0.3
Warrior	0.55	0.45

V. RESULTS AND DISCUSSION

A. System Comparison

In Table VII, it shows the difference between the previous version of the system and the proposed system. Shen *et al.* [5] proposed three specific types of frames to apply on different situation for back-end processing, and designed some functions for user interaction. In score presentation, it gave the shape score to represent the user’s pose similarity compared to instructor. In the proposed system, it divided the Yoga movements into dynamic and static regions and presented different types of scores in these regions for more considerations, in functions, it emphasized how to effectively guide user on doing the poses, and the function lets users get to start with Yoga more quickly.

TABLE VII. DIFFERENCE IN TWO SYSTEMS

	Shen <i>et al.</i> [5]	Proposed System
Concepts	Initial frame	Duration time
	Keyframes	Dynamic regions
	Sync frames	Static regions
Functions	Start	Hint message
	Skeleton	Hint music
	Arrows	
Score Presentation	Shape_score	D_{score} , S_{score}

B. Score Comparison in Different Score Presentations

To show the user’s overall performance, the final scores for different Yoga exercises are shown in Table VIII. The D_{score} for each dynamic region and S_{score} for each static region in different Yoga exercises are shown in Fig. 6. Fig. 7 shows the shape_score of each pose. The test user is

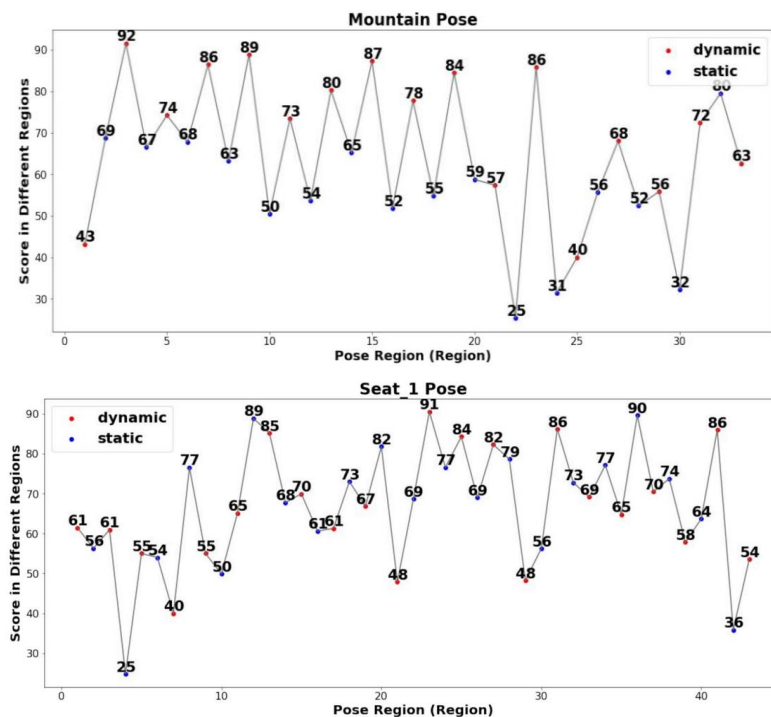
the lazy mode user mentioned in the previous work [13], which means this user simulated the speed of an elderly person to do yoga exercises, to compare the differences in the score presentation between two experimental results.

In Fig. 7, the presented shape_score emphasizes the similarity in posture between the instructor and the user. If the posture similarity is high, the shape_score will be high, but it has a limited meaning as it does not consider other factors such as time or speed of the yoga exercises. In contrast, in Fig. 6, the presented S_{score} compares the time taken by the instructor and the user to perform a static movement, to observe whether the user’s movement time falls within the standard range. The D_{score} , on the other hand, uses the time as a factor to observe whether the user is performing the dynamic movement too quickly or too slowly.

In Fig. 6, these two new score indicators consider the time element in each movement, which allows for a more diverse presentation on the overall score, if the user don’t control their time properly during static movements, it will result in a slight penalty in their score. In contrast, for dynamic movements, in addition to penalty points, positive score feedback can also be given. Hope that users not only maintain the correct posture but also ensure that their movement time is within the standard range.

TABLE VIII. FINAL SCORES IN DIFFERENT YOGA EXERCISES

Poses	Final Scores
Mountain	67.96
Seat_1	66.46
Seat_2	70.20
Side_bend	66.25
Warrior	62.17



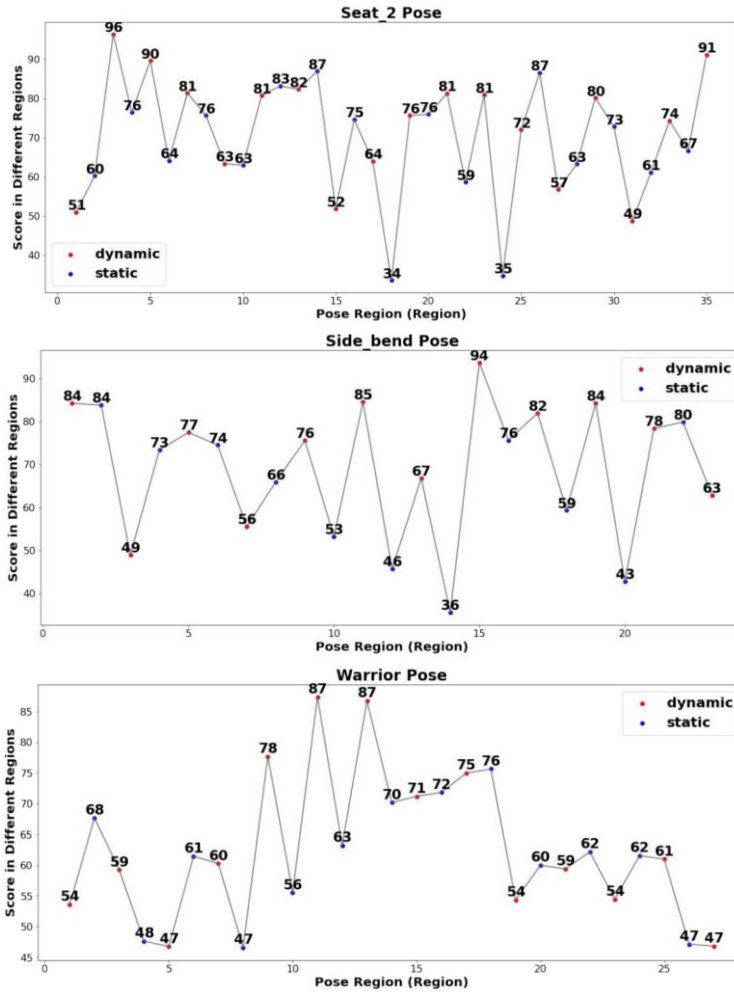
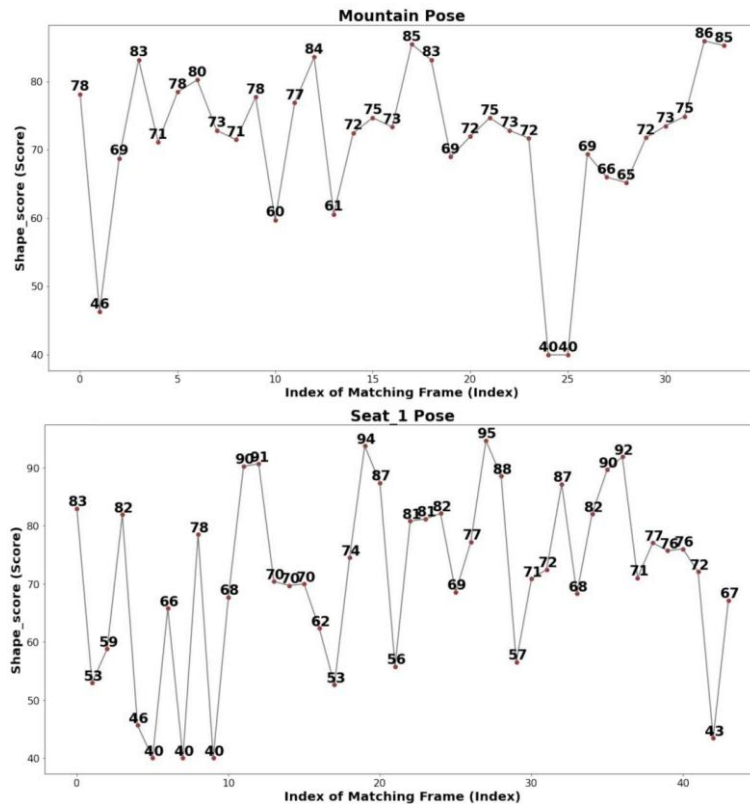


Figure 6. D_{score} and S_{score} in “Mountain”, “Seat_1”, “Seat_2”, “Side_bend”, “Warrior” poses respectively.



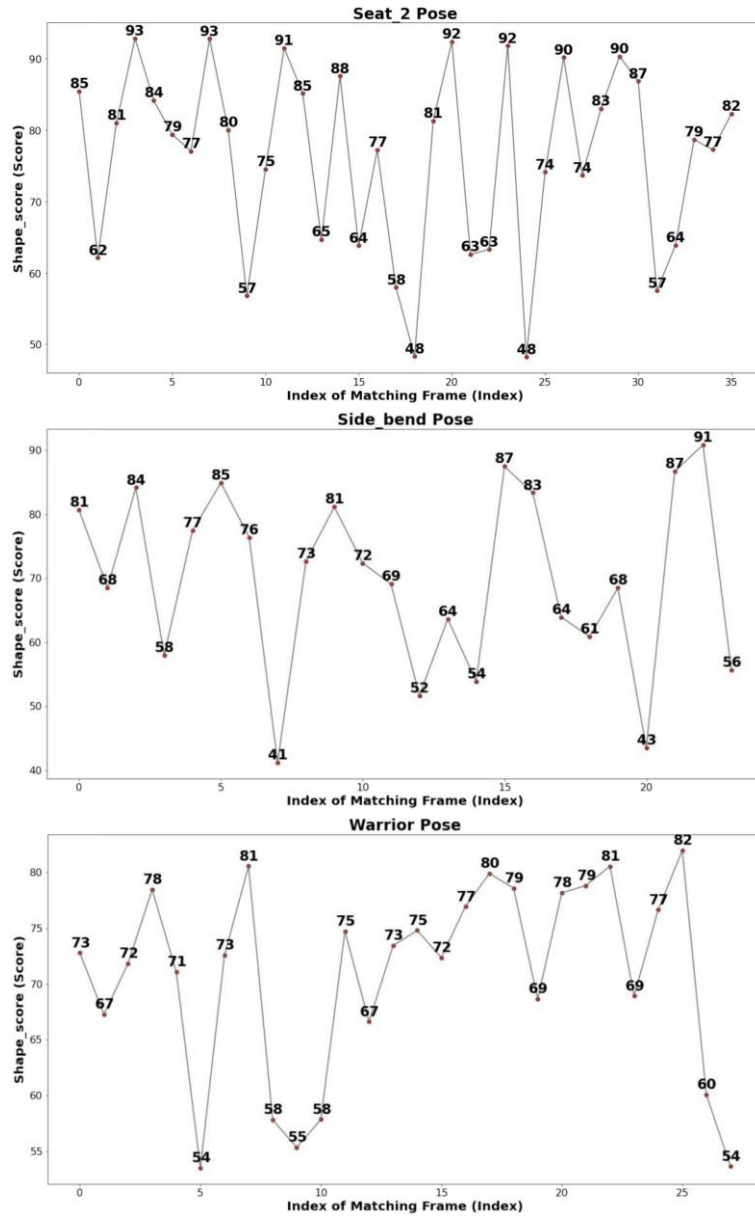


Figure 7. Shape_score in “Mountain”, “Seat_1”, “Seat_2”, “Side_bend”, and “Warrior” poses respectively

VI. CONCLUSION AND FUTURE WORK

For the proposed self-practice Yoga exercise system, the design provides more functions, including hint message and hit music in guidance and suggestions for users, and the functions help the users to improve their Yoga exercises more. The applied functions use the score formula that considers time, static and dynamic factors in postures. For users to practice Yoga exercises, it is very important to control the time of posture’s movements. In the static region, how long the posture needs to be maintained, and in the dynamic region, how fast the speed of movement changes, need to pay attention for users. Finally, the proposed guidance and hint functions developed for the self-practice Yoga exercise system performs effectively.

In the future work, the system will be devoted to providing more functions to increase system versatility and improve the back-end algorithms to achieve more fps

performance in the dynamic motions. In addition, there will be a chance to implement the heart beat sensor or breathe sensor for detecting and analyzing the user’s physiological performance, providing more complete information for the scoring system or hint functions to improve the scoring presentation and hints on users in the system.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Wan-Chia Huang conducted the research and wrote the paper. Cheng-Liang Shih analyzed the data. Irin Tri Angraini provided the dataset. This research was advised by Professor Nobuo Funabiki and Professor Chih-Peng Fan. All authors had approved the final version.

FUNDING

This work was financially supported partly by the National Science and Technology Council under Grant No. NSTC 111-2218-E-A49-028.

REFERENCES

- [1] OpenPose: Real-time multi-person keypoint detection library for body, face, hands, and foot estimation. [Online]. Available: <https://github.com/CMU-Perceptual-Computing-Lab/openpose>
- [2] C. Zhou and W. Li, "Pose comparison based on part affinity fields," in *Proc. 2019 IEEE 2nd International Conference on Information Communication and Signal Processing (ICICSP)*, 2019, pp. 519–523. doi: 10.1109/ICICSP48821.2019.8958597
- [3] I. T. Anggraini, A. Basuki, N. Funabiki, X. Lu, C. Fan, Y. Hsu, and C. Lin, "A proposal of exercise and performance learning assistant system for self-practice at home," *Advances in Science, Technology and Engineering Systems Journal*, vol. 5, no. 5, pp. 1196–1203, 2020.
- [4] S.-W. Shen, W.-C. Huang, I. T. Anggraini, N. Funabiki, and C.-P. Fan, "Exercise and performance learning assistant system for self-practice dynamic yoga by OpenPose and fuzzy based design," in *Proc. 2022 10th International Conference on Information and Education Technology (ICIET)*, 2022, pp. 16–21. doi: 10.1109/ICIET55102.2022.9778954
- [5] S.-W. Shen, W.-C. Huang, I. T. Anggraini, N. Funabiki, and C.-P. Fan, "Design and implementation of image-sensing based learning assistant system for self-practice dynamic yoga on embedded GPU device," in *Proc. 2023 IEEE International Conference on Consumer Electronics (ICCE)*, 2023, pp. 1–3. doi: 10.1109/ICCE56470.2023.10043552
- [6] Y. Hirasawa, N. Gotoda, R. Kanda, K. Hirata, and R. Akagi, "Promotion system for home-based squat training using OpenPose," in *Proc. 2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, Takamatsu, Japan, 2020, pp. 984–986. doi: 10.1109/TALE48869.2020.9368366
- [7] S. Qiao, Y. Wang, and J. Li, "Real-time human gesture grading based on OpenPose," in *Proc. 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, Shanghai, China, 2017, pp. 1–6. doi: 10.1109/CISP-BMEI.2017.8301910
- [8] Y.-C. Li, C.-T. Chang, C.-C. Cheng, and Y.-L. Huang, "Baseball swing pose estimation using OpenPose," in *Proc. 2021 IEEE International Conference on Robotics, Automation and Artificial Intelligence (RAAI)*, Hong Kong, 2021, pp. 6–9. doi: 10.1109/RAAI52226.2021.9507807
- [9] H.-J. Park, J.-W. Baek, and J.-H. Kim, "Imagery based Parametric classification of correct and incorrect motion for push-up counter using OpenPose," in *Proc. 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*, Hong Kong, China, 2020, pp. 1389–1394. doi: 10.1109/CASE48305.2020.9216833
- [10] P. Jafarzadeh, P. Virjonen, P. Nevalainen, F. Farahnakian, and J. Heikkinen, "Pose estimation of hurdles athletes using OpenPose," in *Proc. 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, Mauritius, Mauritius, 2021, pp. 1–6. doi: 10.1109/ICECCME52200.2021.9591066
- [11] K. Abe, K.-I. Tabei, K. Matsuura, K. Kobayashi, and T. Ohkubo, "OpenPose-based gait analysis system for Parkinson's disease patients from arm swing data," in *Proc. 2021 International Conference on Advanced Mechatronic Systems (ICAMechS)*, Tokyo, Japan, 2021, pp. 61–65. doi: 10.1109/ICAMechS54019.2021.9661562
- [12] S.-W. Shen, W.-C. Huang, I. T. Anggraini, N. Funabiki, and C.-P. Fan, "Design of OpenPose-based of exercise assistant system with instructor-user synchronization for self-practice dynamic Yoga," in *Proc. the 10th International Conference on Computer and Communications Management (ICCCM)*, 2022.
- [13] W.-C. Huang, C.-L. Shih, I. T. Anggraini, N. Funabiki, and C.-P. Fan, "Human's reaction time based score calculation of self-practice dynamic yoga system for user's feedback by OpenPose and fuzzy rules," in *Proc. the 11th International Conference on Information and Education Technology (ICIET 2023)*, 2023, pp. 577–581. doi: 10.1109/ICIET56899.2023.10111121

Copyright © 2023 by the authors. This is an open access article distributed under the Creative Commons Attribution License ([CC BY-NC-ND 4.0](https://creativecommons.org/licenses/by-nc-nd/4.0/)), which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made.