Chest Compression Evaluation based on Pose Estimation

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Abstract: - Correct and prompt performance of cardiopulmonary resuscitation yields improvements in mortality and social return rates. Chest compression, a vital cardiopulmonary resuscitation technique, requires regular re-education for skill maintenance. Training with a manikin is feasible for chest compression, but assessing proficiencies without an expert presents challenges. This study aims to facilitate autonomous chest compression training even without expert supervision based on pose estimation. Twenty subjects were recruited for the training and successive performance evaluation of chest compression on a sensor-equipped training manikin, and the corresponding videos were recorded simultaneously. A system was developed to analyze chest compression movements through pose estimation on recorded videos for evaluating interruption presence, compression count, compression tempo, compression depth, and compression recoil. Through comparing three pose estimation models, OpenPose demonstrated the best performance, achieving accuracy rates of 67.08%, 56.67%, 61.25%, 39.17%, and 33.75% for the detection of interruption presence, compression count, appropriate tempo count, appropriate depth count, and appropriate recoil count, respectively. Additionally, posture analysis during compression, unattainable with the sensor-equipped manikin, revealed effectiveness in shooting at a position shifted 45 degrees from the front. The proposed method may serve as a tool for completely automated CPR chest compression training, anticipating an increase in citizens proficient in cardiopulmonary resuscitation.

Key-Words: - cardiopulmonary resuscitation, chest compression, compression count, deep learning, pose estimation, and sudden cardiac death.

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1 Introduction

Considering the requirement of prompt response in cases of cardiac or respiratory arrest, cardiopulmonary resuscitation (CPR) can significantly improve mortality and social return rates if administered promptly before an ambulance arrives. Data from the Japan Ministry of Internal Affairs and Communications reveals insights into the nationwide occurrences of cardiac and respiratory arrest injuries and diseases in Japan, indicating that CPR doubles the survival rate one month later while tripling the social return rate, [1].

Understanding and correctly executing the procedures and techniques of CPR is essential for life-saving. Information on CPR procedures is available in CPR books, medical associations, emergency medical personnel, driving schools, and various training courses. One critical aspect of CPR is the performance of high-quality chest compressions, classified as primary life-saving measures. Chest compressions are administered when there is no breathing or abnormal breathing, targeting the lower half of the sternum to achieve a chest sink of 5 cm, not exceeding 6 cm. The recommended chess compression rate is 100–120 compressions per minute, ensuring complete chest recoil after each compression, [2]. Additionally, it is crucial to avoid applying force to the chest wall between compressions, and interruptions, [2]. European Resuscitation Council also advises extending elbows straight and compressing vertically, [3].

However, it has been found that high-quality CPR improves survival from cardiac arrest, including adequate rate and depth of chest compressions, full chest recoil between compressions, minimum interruptions in chest compressions, and the avoidance of excessive ventilation, [4]. In a study on CPR during out-of-hospital cardiac arrest [5], chest compressions were neglected half of the time, and a significant portion of compressions were too shallow. Consequently, maintaining CPR skills necessitates regular chest compression practice for both the public and emergency lifesavers. While it is possible to assess the tempo and depth of chest compressions using a training manikin with a pressure sensor, its expensive nature poses a challenge to widespread use. Although chest compression training with inexpensive manikins is conducted in places like driving schools, visual evaluation limitations and the difficulty in measuring its effectiveness persist. Considering the large number of cardiac arrhythmic events, training non-experts who can perform chest compression and maintain their skills through reviewing with a low-cost and easily reachable tool is important.

This study aims to develop an AI-powered chest compression evaluation system using pose estimation. This system will facilitate the assessment and verification of chest compression skill proficiency even without expert oversight, with the expectation that recursive self-training can lead to more efficient chest compression skill improvement.

Several studies have been performed on posture-based CPR evaluation systems. In [6], Microsoft's Kinect V2 was used for motion capture, comparing the time and posture required for different chest compression interruption procedures. They found significant differences between experts and non-experts [6]. Similarly, an RGB-D (Kinect) sensor was employed for motion capture, evaluating compression tempo and depth using an approximate sine wave model from skeletal data, [7]. Meinich-In [8], an experiment with chest compression modeling was performed using Kinect, demonstrating acceptable measurements of sternum compression depth with a smartphone's depth camera and accelerometer sensor. In [9], a VR training simulator prototype was developed with pose estimation using OpenPose and a web application evaluating chest compression tempo, depth, recoil, compression position, and elbow angle. Pose estimation was conducted using an infrared progress detector and OpenPose, creating a quality evaluation system for chest compression information visualization, [10]. In research except [11], specialized cameras and sensors were used for easing pose estimation. Though a web application was developed in [11], it demanded a PC equipped with a high-performance CPU and GPU. In this study, we expect to realize a chest compression analysis system using an embedded camera and processing unit of a smartphone. Therefore, this system should be computationally feasible and easy to use by non-experts.

This study aims to facilitate autonomous chest compression training even without expert supervision. Twenty subjects were engaged in chest compression on a sensor-equipped training manikin, and video recording was conducted simultaneously. A system was developed to analyze chest compression movements through pose estimation on recorded video, evaluating interruption presence, compression count, compression tempo, compression depth, and compression recoil, respectively.

2 Materials and Methods

2.1 Data

This study recruited twenty subjects (15 males and 5 females) to get the chest compression videos for training and validation. They performed chest compression training on a manikin equipped with a pressure sensor, Resusci Anne QCPR, Laerdal Medical Corp., Norway. The report of Skill Reporter of the manikin equipment serves as the golden standard for evaluation. The data were obtained in 12 scenarios as listed in Table 1, each lasting one minute, both before and after the instruction. Tempo and compression strength were varied during the training. This study has been approved by the Institution Review Board of The University of Aizu, and performed based on the Declaration of Helsinki.

As shown in Figure 1, the distance between the camera and the training manikin was 165 cm, and the camera was positioned at a height of 85 cm. The camera was set at an angle of 45 degrees from the front of the participant. The video started with the participant's hands on the training manikin. Videos were recorded at frame per second (FPS) =25 by two GoPro HERO10 Black cameras made by GoPro Inc., USA.

Table 1. Types of Executed Chest Compression

Number	Executed chest compression
1	Normal compressions without training
2	Slow and weak compression without training
3	Slow and strong compression without training
4	Fast and weak compression without training
5	Fast and strong compression without training
6, 7	Normal compression after training (twice)
8	Slow and weak compression after training
9	Slow and strong compression after training
10	Fast and weak compression after training
11	Fast and strong compression after training
12	Intentional poor compression

Fig. 1: Experimental scene, GoPro HERO10 Black camera, and Resusci Anne QCPR manikin

2.2 Pose Estimation Models

Chess compression can be well analyzed using pose estimation models by tracking keypoints of hands to get the features of chest compression. However, automatically analyzing human posture (pose) from images or videos is one of the important challenges in computer vision. Pose estimation and hand tracking are widely used to analyze the movements of humans and animals, and to create 3D models. Recently, researches on pose estimation using deep learning have been actively conducted, and technologies capable of estimating poses quickly and with high accuracies have been developed. The following steps are listed about pose estimation and hand tracking using deep learning.

(a)Preprocessing images or videos: this involves processing images or videos as input and adjusting their sizes, colors, and formats.

(b)Keypoint detection: from the preprocessed images or videos, keypoints that represent the positions of various human body parts are detected including joints or endpoints, such as the head, neck, shoulders, elbows, hands, waist, knees, and feet. The number and position of keypoints vary depending on the used pose estimation model. Keypoint detection often involves the use of deep learning models such as CNNs.

(3)Posture prediction: from the detected keypoints, the human posture is estimated. Posture prediction often involves methods such as connecting keypoints with lines.

In this study, OpenPose [12], YOLOv8-pose [13] and MediaPipe [14] were utilized to get the features for analyzing the chest compression of the subjects. Hand tracking was also employed by OpenPose [12] and MediaPipe [14]. Then, the performance of these models was compared.

OpenPose, proposed in 2018, can perform real-time two-dimensional pose estimation for multiple individuals [12]. It can detect 25 keypoints for pose and 21 keypoints for hand. Adopting a bottom-up approach, it utilizes vgg-18 [15] in the feature vector extraction layer (F). OpenPose outputs both a heatmap and a Part Affinity Field (PAF). The PAF assigns a two-dimensional vector along the line segment connecting keypoints to each pixel. This allows for the representation of the relationship between keypoints, proving effective for keypoint matching and occlusion handling, [12].

MediaPipe, released by Google in 2020, enables real-time three-dimensional pose estimation for a single individual. The keypoints that can be detected are 32 for pose and 21 for hand, referred to as BlazePose and BlazePalm [16], respectively. A top-down approach is adopted, with MobileNetV2 [17] used for feature extraction. Unlike the OpenPose models, MediaPipe processes solely on the CPU, allowing it to run on a standalone smartphone. It can determine 3-dimension coordinates from two-dimensional images. The architecture consists of a Detector, which extracts individuals from images, and an Estimator, which outputs the coordinates of keypoints. The Estimator uses a Heatmap only during training, and calculates the locations of keypoints directly during inference, thereby achieving fast inference, [16], [17].

2.3 Pose Estimation Models

The vertical coordinate of the right wrist, among the key points estimated by each model, was targeted for peak detection as illustrated in Figure 2. Peaks in the y-coordinate data were treated as depth for local maximum values and recoil for local minimum values. The open-source Python libraries including SciPy's scipy.ndimage.filters.maximum_filter function [18] and scipy.signal.find_peaks function [19], were used for peak detection. The maximum_filter function replaced the coordinate data with the maximum and minimum values within a certain window around it, reducing the local maximum and minimum values of the coordinates. Subsequently, the find_peaks function was used to detect peak clusters within the coordinate data. Peaks were used for successive analysis including interruption detection, and the evaluation of compression count and tempo.

2.4 Pose Estimation Models

Interruptions in chest compression are determined when there is no compression for more than one second as shown in Figure 3. In this study, interruptions were judged in the detected peak clusters under the following criteria.
(a) When the temporal difference between adjacent peaks in depth is greater than FPS.
(b) When the right wrist moves outside a predefined pixel area on the x-axis, marked from the center of the compression position on the training manikin.

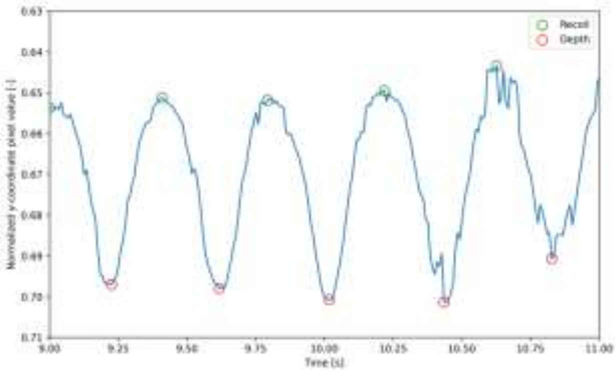

Fig. 2: Example of peak detection

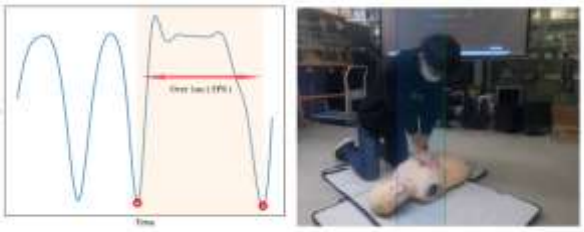

Fig. 3: Processing of the presence interruptions

2.5 Pose Estimation Models

The measurement of compression tempo is one of the most important tasks in the evaluation of chest compression because compression tempo may directly reduce the efficacy of chest compression. The appropriate tempo for chest compressions is 100 to 120 times per minute, [2]. In this study, the count of chest compressions was determined from the results of peak detection. To avoid misdetection, we removed the erroneous peaks when the right hand was away from the compression position, and noise was detected in the detected depth peak clusters. This reduced the numbers of false detection. The tempo of chest compressions was evaluated from the following two indexes.

Mean tempo: The average count of compressions per minute.

$$Mean\ tempo = \frac{Count\ of\ compressions \times fps \times 60}{Number\ of\ frames} \quad (1)$$

Appropriate count of tempos: Calculate the count of times the compression is applied in the proper tempo in a video.

$$\frac{fps \times 60}{120} \leq Tempo \leq \frac{fps \times 60}{100} \quad (2)$$

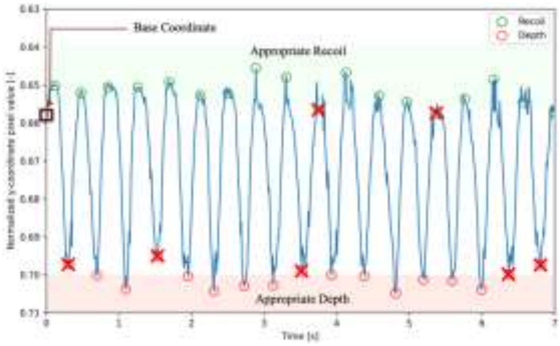

Fig. 4: Depth and recoil evaluation method

2.6 Evaluation of Compression Depth and Recoil

The compression depth and recoil are important factors for the successful delivery of chest compression. Appropriate chest compressions require a depth of more than 5 cm and a recoil that returns the chest to its original height. In this study, the starting position was where the subject touched the training manikin, so the vertical coordinate of the right wrist at frame zero was used as a reference to set the depth and recoil lines. As illustrated in Figure 4, the count of appropriate depths was evaluated when the vertical coordinate of the depth peak cluster was larger than the depth line in pink. Similarly, the count of appropriate recoils was evaluated when the vertical coordinate of the recoil peak cluster was smaller than the recoil line in green. In Figure 4, the qualified compression depth and recoil are marked with circles, while the unqualified ones with crosses.

2.7 Evaluation of Posture During Compression

During chest compressions, it is recommended to extend the elbows straight and compress vertically against the training manikin, [3]. In this study, the posture during compression was evaluated from the following three perspectives.

Stability of Compression Posture: For each frame, the x (horizontal) coordinate of the key points at the left and right shoulders, elbows, and wrists were used with the following autocorrelation function. By setting the time lag (k) to the average tempo, the stability of the posture and tempo during compression was evaluated.

$$\rho_k = \frac{\sum_{t=k+1}^{N}(x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2} \tag{3}$$

$$\text{where } k = \frac{fps \times 60}{Mean\ tempo} \tag{4}$$

and N is the length of the x-coordinate waveform in a key point.

Elbow Angle: For each frame, the angle formed by the elbow was calculated using the cosine theorem for the x and y coordinates of the key points at the right shoulder, elbow, and wrist.

Angle Against the Training Manikin: For each frame, the angle formed by the wrist was calculated using the cosine theorem for the midpoint of the x and y coordinates of the key points at the left and right shoulders and wrists and a point perpendicular to the x-axis at the midpoint of the wrist.

The details of how to calculate the elbow angle (α) and the angle (β) against the training manikin are shown in (5) and Figure 5.

$$\cos\alpha, \beta = \frac{b^2 + c^2 - a^2}{2bc} \tag{5}$$

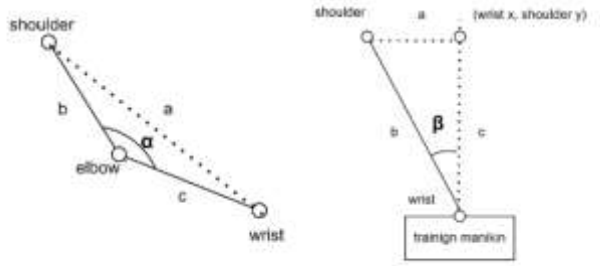

Fig. 5: Definitions of α and β

2.8 Evaluation of Chest Compression Evaluation System

The results of the chest compression evaluation system, executed on the keypoint data from each estimation model and the results of the Skill Reporter as the gold standard, were compared for the accuracies in Interruption presence (IP), Count of compressions (CC), Count of appropriate tempos (CT), Count of appropriate depths (CD), and Count of appropriate recoils (CR). It should be noted that for the comparison, considering the discrepancy between the recorded video and the Skill Report, the comparison was made separately for each video of chest compressions performed by 20 subjects. The accuracy for each item was evaluated using an accuracy defined as follows.

$$Acc = \frac{Number\ of\ videos\ with\ the\ same\ evaluation\ as\ Skill\ Reporter}{Number\ of\ total\ videos} \tag{6}$$

3 Results

3.1 Comparison with Skill Reporter

In this study, pose estimation was performed using OpenPose, YOLOv8-pose, and MediaPipe. In addition, hand tracking was conducted with OpenPose and MediaPipe, targeting the y (vertical) coordinate of the wrist root for peak detection. Table 2 lists the results of the evaluation metrics for each item of chest compression.

Among the five models, OpenPose and YOLOv8-pose demonstrated the same performance in detecting the presence of interruptions and validating the count of appropriate depths for chest compression. Considering the count of compressions, YOLOv8-pose exceeded OpenPose with a compression count accuracy of 57.08%. However, OpenPose was the best for the count of appropriate tempos and recoils. MediaPipe-hand was only inferior to OpenPose and YOLOv8-pose for the count of appropriate depths accuracy, but its performance for other items was low.

3.2 Comparison by Tempo and Strength

In this experiment, data was collected by changing the tempo and strength of the compression. Table 3 lists the results of the evaluation items of chest compression from the aspects of tempo and strength in OpenPose. The number in the pattern is the type number of chest compressions. When the tempo and strength were normal, the accuracy for analyzing the presence of interruptions (IP), the count of compressions (CC), and the count of appropriate recoils (CR) were higher compared to those of other protocols. However, the accuracies for the count of appropriate tempos (CT) and depths (CD) were the worst. When comparing by tempo, it was found that the accuracy for the presence of interruptions (IP) was very poor when the tempo was slow. Conversely, when the tempo was fast, the accuracy of the count of compressions resulted in poor performance. When comparing with the strength of compression, it was found that the depth of compression could not be judged when the compression was strong. As the distance between the camera and the subject varies, the depth measurement has worse accuracy, so appropriate tempos and compression recoil could not be accurately determined.

Table 2. Accuracies of the assessment items by each model

Models \ Items	IP (%)	CC (%)	CT (%)	CD (%)	CR (%)
OpenPose	**67.08**	**56.67**	**61.25**	**39.17**	**33.75**
OpenPose-hand	65.00	55.42	60.00	35.83	32.92
YOLOv8-pose	67.08	57.08	57.92	35.00	33.33
MediaPipe	42.08	36.25	49.58	24.17	18.33
MediaPipe-hand	41.67	24.17	58.33	30.93	19.58

Table 3. Comparison of tempo and strength assessment items using OpenPose

Pattern \ Items	IP (%)	CC (%)	CT (%)	CD (%)	CR (%)
Normal (1,6,7)	96.67	88.33	45.00	31.67	51.67
Slow (2,3,8,9)	48.75	58.75	78.75	51.25	36.25
Fast (4,5,10,11)	80.00	45.00	71.25	42.50	26.25
Weak (2,4,8,10)	65.00	56.25	72.5	66.25	26.25
Strong (3,5,9,11)	63.75	47.50	77.50	37.50	36.25

3.3 Posture Evaluation Result

In the evaluation of posture, the average of all subjects was taken for the stability of the compression posture as shown in Figure 6, the angle of the elbow, and the angle against the training manikin for each type of chest compression performed.

The angle of the elbow and the angle against the training manikin also showed in Figure 7 that the elbow was extended and could be compressed vertically before and after the training. In this study, the shooting was done from a position shifted 45 degrees from the front, and it was found that it can be differentiated from the correct compression posture.

4 Discussion

In this study, evaluations were performed for each video. Therefore, if the results of the proposed evaluation system and the Skill Report, i.e., the golden standard, do not match, it is considered unacceptable. Consequently, a slightly lower accuracy is inevitable, but the evaluation of tempo and depth remains a future challenge. Despite a high accuracy in the count of chest compressions during normal tempo evaluation, the results were low during abnormal tempo evaluation. This is believed to be a problem caused by the low FPS and maximum_filter function. When detecting peak clusters, the maximum_filter function finds the minimum and maximum values from a certain area. However, if the FPS is small, the timing of the actual compression may be slightly inaccurate because the actual peaks cannot be accurately captured. The limitation of this study is that the influence of different FPS was not studied. Therefore, the FPS should be improved in the future application.

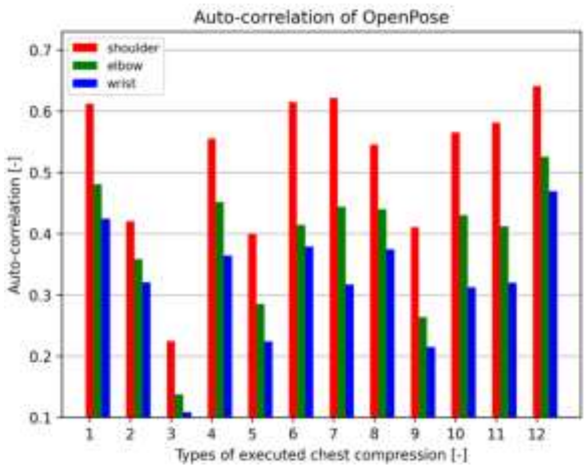

Fig. 6: Postural stability result

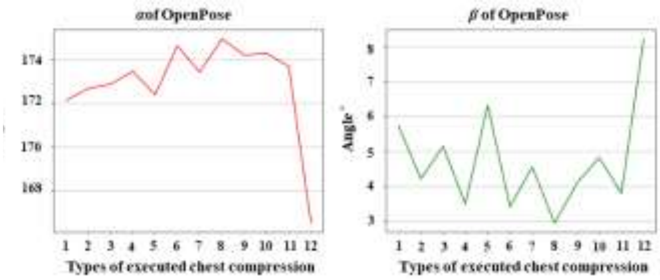

Fig. 7: Results of the elbow angle α and the angle β against the training manikin

In the evaluation of depth, it cannot be well evaluated when the compression is strong. This may be primarily caused by the wrist keypoints varying with the pose estimation model and shooting conditions. Tuning suitable hyperparameters for each estimation model and attention to clothing should be paid. In addition, segmentation is being considered as another method of depth evaluation in the future.

In the posture evaluation, the results for α and β showed a decline during the second normal compression following training, but this is within the margin of error. A shift of 45 degrees, as opposed to a frontal view, allows for an assessment of whether vertical compression against the training manikin is possible, thus it is deemed a viable method for evaluating chest compression posture.

5 Conclusion

In this paper, we proposed a system for the evaluation of chess compression based on motion analysis modules. Twelve patterns of chest compression were performed by twenty individuals, and the chest compression evaluation system's accuracy was compared using OpenPose, YOLOv8-pose, and MediaPipe, based on the Skill Reporter from Laerdal. The accuracies of the chest compression evaluation systems using OpenPose, YOLOv8-pose, and MediaPipe were confirmed based on the golden standard of Skill Reporter. The results using OpenPose were superior for analyzing the presence of interruptions, the count of compressions, the appropriate count of tempos, the appropriate count of depths, and the appropriate count of recoils. The evaluation of tempo and depth is unsatisfying; therefore, alternative methods should be considered. In the pose estimation using OpenPose, stability was lost when compressing was weak and fast. It was found that the angle of the elbow and the angle towards the manikin improved after the training, so the method of shooting from a 45-degree position from the front was effective. Compared with previous studies, [7], [8], [9], [10], [11], the proposed system can perform the evaluation of chess compression using generic video cameras with satisfying evaluation accuracies. This study also provided the basis for an evaluation system for the recursive training of chest compression using a smartphone application. We expect this study will enable the prompt delivering of chest compression on subjects experiencing malignant ventricular fibrillation and tachycardia, and therefore improve their survival rate and social return rate.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Xin Zhu, Yumiko Kaneko, and Ken Iseki proposed the conceptualization and designed the research plan. Xin Zhu and Yumiko Keneko prepared the research fund application documents. Ken Iseki provided the experiences of CRP and the standard device for the evaluation of CRP. Yuki Iijima and Xin Zhu carried out the experiments, performed data curation and project administration, developed the software of algorithms, wrote the original draft of the manuscript, and prepared the final version. Lei Jing and Yan Pei provided experiences in the development of algorithms. Xin Zhu supervised and validated the whole research procedure.

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Conflict of Interest

The authors have no conflicts of interest to declare.