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Evaluation of Skills in Cardiopulmonary Resuscitation (CPR) Using Microsoft Kinect

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Abstract: Cardiopulmonary resuscitation, commonly known as CPR, is an emergency procedure that normally combines chest compression with artificial ventilation in an effort to preserve intact brain function manually until further measures can be taken to restore spontaneous blood circulation and breathing in a person who is in cardiac arrest. In this study, we evaluated the skills of CPR practitioners on the basis of kinematic data obtained from their body movements while performing CPR. In particular, we used a Microsoft Kinect sensor to evaluate CPR performance by new and more experienced practitioners and to analyze CPR skill-building techniques. Such measurement using the Kinect sensor enabled detailed information about motion at body joints to be displayed quickly and objectively, thus facilitating identification of any problems. However, we could not confirm gesture recognition and detailed motion analysis based on using a high-speed camera to capture three-dimensional (3-D) motion of the entire body, we determined the Kinect sensor to be an easily applied evaluation tool that can provide body-motion information quickly and thus serve as an objective index for evaluating CPR performance.

Key words: Skill science, kinect, CPR, acceleration sensor, high-speed video camera.

Nomenclature

AE	Absolute error $= \lvert D_k - D_c \rvert$ (mm)
D_c	Chest compression depth measured by high-speed video camera (mm)
D_k	Chest compression depth measured by Microsoft Kinect (m)
F_a	Peak frequency measured by acceleration sensor (Hz)
F_k	Peak frequency measured by Microsoft Kinect (Hz)
RE	relative error = $D_k / D_c \times 100$ (%)
t	time (s)
X	Coordinate direction of left elbow indicated in Fig. 2
Y	Transverse coordinate of left elbow indicated in Fig. 2
Z	Vertical coordinate of left elbow indicated in Fig. 2
α_x	Acceleration in X-direction (m/s^2)
α_y	Acceleration in Y-direction (m/s^2)
α_z	Acceleration in Z-direction (m/s^2)

1. Introduction

Microsoft Kinect is a line of motion-sensing input devices for Xbox 360 and Xbox One video-game consoles and Windows PCs. Kinect relies on Microsoft software technology and range-camera technology, which uses a system that can interpret specific gestures. This completely hands-free control of electronic devices was enabled by using an infrared projector and camera with a special microchip to track the three-dimensional (3-D) movement of objects and individuals [1, 2]. Microsoft Kinect is an inexpensive, unobtrusive, and easily applied technology that is useful for monitoring subjects during clinical features [3-6]. Microsoft Kinect for the Windows software development kit (SDK) includes skeletal tracking, whereby 20 virtual anatomical joint trajectories are extracted from a depth map using a pixel-level semantic-segmentation algorithm [7-10].

Researchers examined the accuracy level of the Kinect v1 skeleton joints for the assessment of various temporal and spatial gait parameters during treadmill walking [11]. Using the Kinect sensor, they concluded that the accuracy varies depending on the calculated gait parameters and that the Kinect sensor may follow

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the trend of the joint trajectories but with substantial error bars for knee and hip joints. In addition, the accuracy of Kinect v1 has been evaluated for measuring movement in people with Parkinson's disease [12]. The main results of that study revealed that Kinect can accurately measure timing and gross spatial characteristics of clinically relevant movement. However, it cannot achieve the same spatial accuracy for smaller movements [13, 14]. The accuracy of the skeleton joints positions also has been analyzed during static postures of daily activities for Kinect v1 and Kinect v2 [15-20].

Cardiopulmonary resuscitation, commonly known as CPR, is an emergency procedure that normally combines chest compression with artificial ventilation in an effort to preserve intact brain function manually until further measures can be taken to restore spontaneous blood circulation and breathing during cardiac arrest [21]. The use of CPR is indicated for those who are unresponsive and who are either not breathing or breathing abnormally, such as in agonal respiration (breathing only in occasional gasps), possibly due to cardiac arrest [22].

In this study, we paid attention to the motions of skillful CPR practitioners and attempted to find a comparatively simple and easy method for extracting the characteristics and skills that experts have in common. We aimed at building a quantitative model showing a behavior pattern and developing an exercise-support system for new CPR practitioners and for those who want to improve their CPR skills. We first examined whether objective evaluation could be performed using a Microsoft Kinect sensor on a level comparable to that achieved by image-based two-dimensional (2-D) motion analysis with 3-axis acceleration measurements. We also compared the two methods for studying chest compression in CPR.

To evaluate motions of both the experienced and the new CPR practitioners, we used a high-speed video camera and an accelerometer capable of performing 3-axis measurements. The video recording (subjected to quasi-2-D image processing) together with the acceleration values allowed us to verify motion analysis from simultaneous measurements made using a Microsoft Kinect sensor.

The Microsoft Kinect sensor measurements enabled detailed motion information generated at the sensor-installation points to be displayed quickly, thus making any problems easily and objectively isolated. Although we could not use the Microsoft Kinect measurements to verify the detailed motion of the entire body as simultaneously recorded in the 2-D imagery from the high-speed video camera, we did confirm that the Kinect sensor is an evaluation tool that is easy to set up and can quickly provide objective exercise information in relation to various body joint positions. Also, this method can function as an exercise-support system for new CPR practitioners and for those who aim to improve their CPR skills. The paper is organized as follows: Section 2 explains the experimental apparatus and method; Section 3 presents experimental results and discussion; and Section 4 gives conclusions.

2. Experimental Apparatus and Methods

2.1 Microsoft Kinect Sensor

Microsoft Kinect sensor features a red-green-blue (RGB) camera, a depth sensor, and a multiple-array microphone running proprietary software. The device is capable of full-body 3-D motion capture, facial recognition, and voice recognition. The 3-D scanner system, called Light Coding, uses a type of image-based 3-D reconstruction [7, 8]. The depth sensor consists of an infrared laser projector combined with a monochrome complementary metal-oxide semiconductor sensor, which captures video data in 3-D under any ambient-light conditions [9, 10].

The Kinect system is placed at the two sides of the footpath, and 30-Hz video data are acquired from each Kinect camera using the Microsoft SDK (Beta2 version) and customized software (Microsoft Visual Studio 2012). Kinect's SDK supports a number of programing languages, such as C++, C#, and Visual Basic.NET. One data frame contains the 3-D positions of 25 joints over time, which yields a 75-dimensional vector. The 25 joints include head, shoulders, elbows, wrists, hands, spine, hips, knees, ankles, and feet (Fig. 1). Fig. 2 shows the locations of body joint centers estimated by Microsoft Kinect during CPR. The default RGB video stream uses 8-bit Video Graphics Array (VGA) resolution (640 × 480 pixels), but the hardware is capable of resolutions up to 1,280 × 1,024. The monochrome depth-sensing video stream is in VGA resolution (640 × 480 pixels) with 11-bit depth, which provides 2,048 levels of sensitivity.

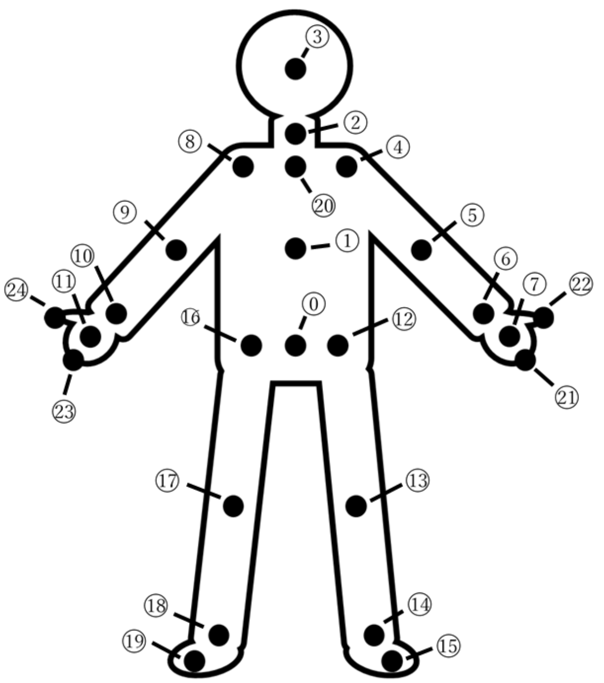


Fig. 1 The 25-joint positions provided by Kinect.

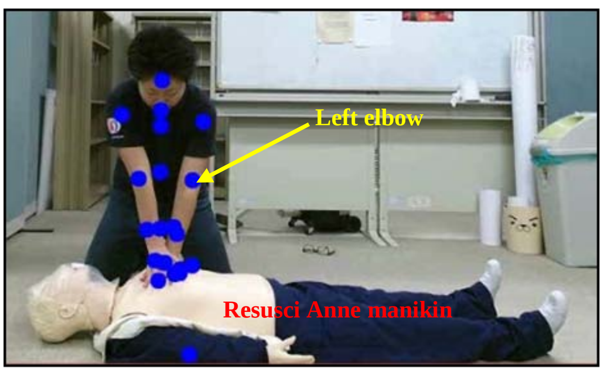


Fig. 2 Locations of body joint centers estimated by Microsoft Kinect during CPR.

2.2 High-Speed Video-Camera Recording

Fig. 3 shows a schematic diagram of the experimental apparatus and the measuring equipment. For recording motion in quasi-2-D, we used a DITECT HAS-L1 Digital high-speed video camera, capable of recording 500 images per second, connected by cable to a desktop computer and to a light. We calibrated the camera, set it up facing the front of the test subject, and captured a series of movements of the left elbow during CPR chest compressions, while the computer recorded the images received from the camera.

The control-point markers used for image analysis were attached by the tape to test the subject's main body parts. To prevent the marking tapes from shifting during measurement, elbow pads and knee pads were used on body joints. Throughout the CPR process, the high-speed video camera recorded the image data and streamed it to the computer, where image-analysis software was used to digitize the motion imagery and send it on to a dedicated plotter. During processing of the waveforms, we eliminated data noise, including that produced during image analysis, using a low-pass filter, which selectively removes the high-frequency noise.

2.3 Acceleration Measurement

We used a MicroStone triaxial accelerometer (external dimensions: 45 × 45 × 18 mm, weight: 5 g, acceleration: ± 20 / ± 60 m/s^2, angular velocity: ± 300 rad/s), to capture data in the X, Y, and Z directions and an ONO SOKKI multichannel data station DS-0264

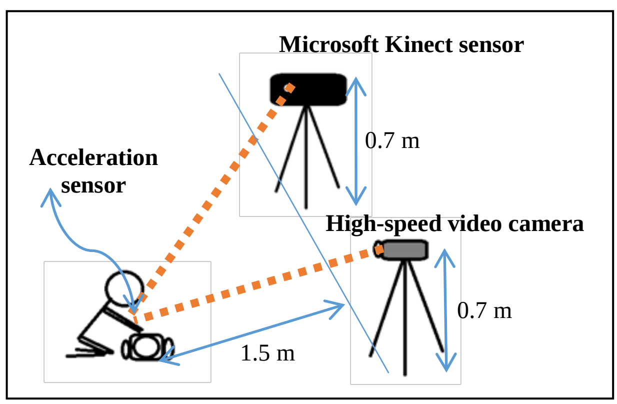


Fig. 3 Experimental apparatus.

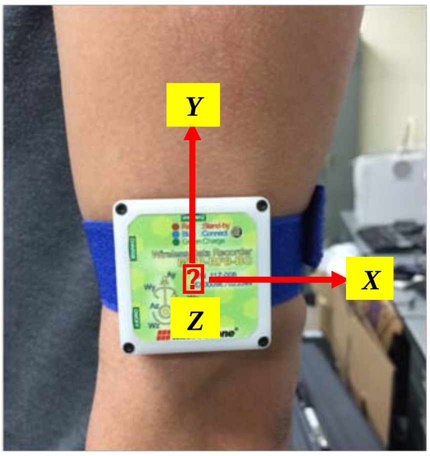


Fig. 4 Left elbow equipped with acceleration sensor.

Fast Fourier Transform (FFT) analyzer. The number of sampling points was 2,048.

We installed the acceleration sensor with machined jigs at one point on the left elbow, where we expected a conspicuous difference in chest compression motion by different CPR practitioners. Fig. 4 shows the coordinate system of the acceleration sensor equipped for the left elbow. We strapped the sensor securely at the measurement point so that it would not move out of place during CPR. The arrows on each of the three axes point in the positive direction. We simultaneously measured the acceleration signal using the Microsoft Kinect sensor and then analyzed the recording. We input the start signal as an external trigger for the acceleration measurement to synchronize the timing of the Kinect recording with the MicroStone measurements.

2.4 Text Subjects

Two male undergraduate university students (height, 171.0 ± 4.0 cm; weight, 65.8 ± 8.8 kg) were selected as the experienced CPR practitioners, and two males aged … and … (height, 168.5 ± 3.5 cm; weight, 67.0 kg ± 9.0 kg) who had no experience in CPR practice were selected as the new practitioners.

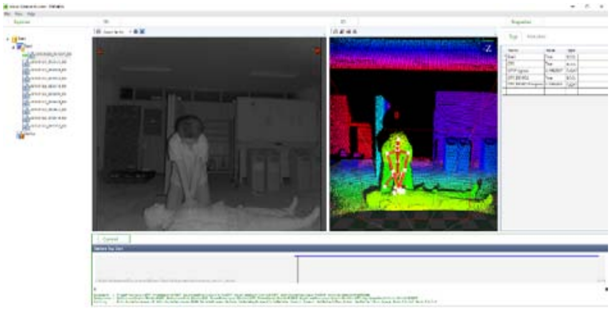
3. Experimental Results and Discussion

To ascertain the accuracy of the experimental results, we compared the clinical features (described in the Section 2) extracted by the Kinect sensors with the reference values obtained by the high-speed video camera and acceleration sensors. In particular, we assessed the spatial and temporal accuracy of Kinect data obtained during CPR chest compressions.

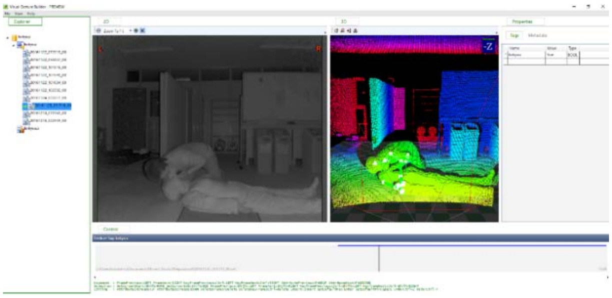
3.1 Accuracy of Motion Analysis by Microsoft Kinect

The Kinect v2 accuracy is measured through salient features considered clinically relevant descriptors of subject's performance. For each exercise, these clinical features are classified as dynamic feature (D.F.) and static feature (S.F.) (Fig. 5). D.F. describes the kinematic goals that subjects have to reach (i.e. lifting of arms or arm lateral tilting), while the S.F. represents the multi-joint posture the subject has to maintain during the execution.

Fig. 6 shows the chest-compression displacements (D.F.) and artificial ventilation (S.F.) during CPR measured by Microsoft Kinect. Fig. 7 shows typical waveforms of the Kinect marker indicating movements of the left elbows of a skilled practitioner (Fig. 7a, showing vertical-axis Y displacement) and of an unskilled practitioner (Fig. 7b) during CPR chest compressions (D.F.).



(a) Dynamic feature: chest compression



(b) Static feature: artificial ventilation

Fig. 5 Clinical features extracted for CPR by Microsoft Kinect.

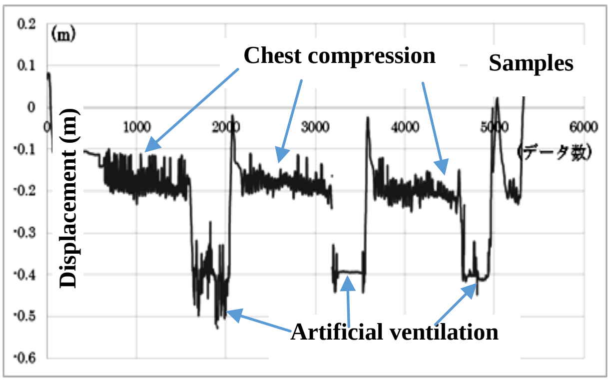
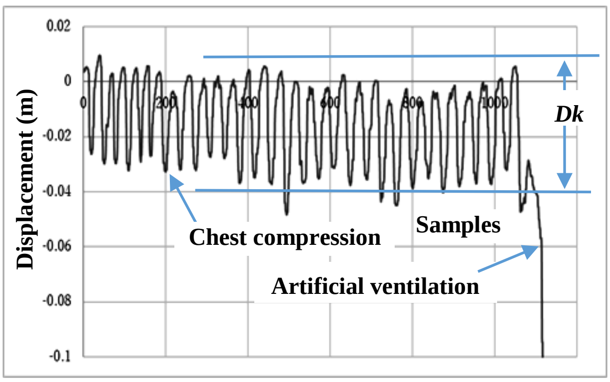
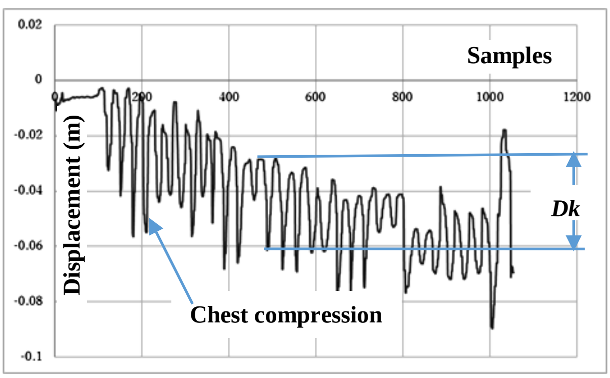


Fig. 6 Left elbow displacement measured by Microsoft Kinect during CPR.



(a) More experienced practitioner



(b) New practitioner

Fig. 7 Left elbow displacements measured by Microsoft Kinect during chest compressions of CPR.

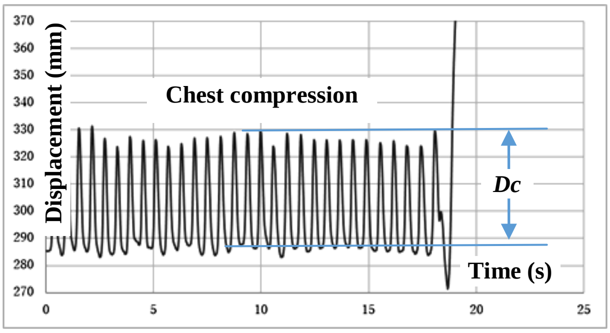
Changes in displacement were observed almost continuously during chest compressions. We found that the displacements recorded for the unskilled practitioner (Fig. 7b) were more unstable and showed slowly decreasing fluctuations during CPR chest compressions compared with those for the skilled practitioner (Fig. 7a). The skilled practitioner's left-elbow displacement in the *Y*-axis direction had a greater change than that in the *X*-axis and *Z*-axis directions. The same tendencies were observed for other test subjects.

3.2 Spatial Accuracy of High-Speed Video-Camera Recordings of CPR Chest Compressions

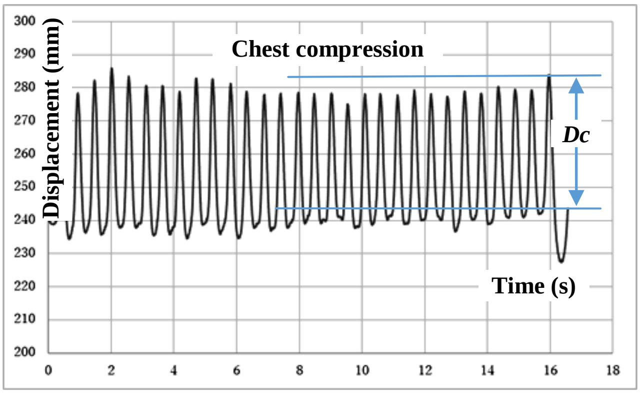
Fig. 8 shows the displacements of the left elbow during CPR chest compressions by experienced practitioner (Fig. 8a) and new practitioner (Fig. 8b). We obtained these results by applying the motion-analysis software to the images recorded using the high-speed video camera. These results are very similar to the results from the Microsoft Kinect analysis of the CPR practitioners and therefore provide evidence of the reliability of the measurements. To record output from the high-speed video camera in this experiment, we used hard disks and set the forwarding width per frame to 0.002 s (recording speed of 500 images per second). Thus, in this analysis, the motion of the marker being shifted at the left elbow was digitalized at intervals of 0.002 s by a dedicated plotter and transferred into the computer. Waveforms that included high-frequency noises generated during the image analysis were smoothed by processing using a low-pass filter with a cutoff frequency of 20 Hz.

To characterize compression depth obtained by analysis of images produced by the Kinect sensor and the high-speed video camera, data for the skilled practitioners (Experts A and B) and the unskilled practitioners (Beginners C and D) were acquired for each of the 10 CPR experimental runs. We obtained average values for CPR chest-compression depths from both the maximum and minimum amplitude of the left-elbow displacements in the *Y*-axis direction, which compressed the chest in the Resusci Anne adult manikin.

In 2010, the American Heart Association and International Liaison Committee on Resuscitation updated their CPR guidelines [21] to recommend a compression rate of at least 100 beats-per-minute and compression depth of at least 5 cm for adults or



(a) More experienced practitioner



(b) New practitioner

Fig. 8 Left elbow displacements measured by high-speed video camera during chest compressions of CPR.

children and 4 cm for infants. These new guidelines can be used as standards for evaluating CPR technique [22]. We found the average compression depth measured by the Kinect device to be ~3.8 cm and by the high-speed video camera, ~4.5 cm. Table 1 shows the averaged values of the compression depth (maximum peak value minus minimum value) calculated for the system together with the peak absolute error (*AE*) and peak relative error (*RE*) and shows the spatial accuracy for each chest-compression depth in terms of peak: *AE* and *RE*.

When we compared the average amplitudes of chest compression (Table 1), we found that the values for the elbow displacements measured by Microsoft Kinect were lower than those for the displacements measured by the high-speed video camera. In addition, the CPR chest compressions done by the skilled practitioners (Experts A and B) fluctuate less than those done by the unskilled practitioners, showing that the skilled practitioners were stable whereas the unskilled practitioners were relatively unstable in CPR chest compressions.

We measured the error of the chest-compression depth for upper and lower displacement during the CPR chest compressions: Maximum *AE* = 1.7 cm, and maximum *RE* = 85.4%. For Beginner C, during the left-elbow displacements measured by Microsoft Kinect during CPR chest compressions, the oscillation of the error is comparable. We measured the maximum error for Beginner C during elbows flexion for both shoulders. Features computed by Kinect follow the trend of the ground-truth signal; in particular, Kinect underestimates the upper (peak) and lower values when the two values are comparable. Although there are systematic fluctuations (removed from Figs. 7 and 8), there is a similar trend of these features for "both" recording systems (Kinect and video).

3.3 Temporal Accuracy of Triaxial-Accelerometer Recordings of CPR Chest Compressions

Fig. 9 shows typical waveforms measured by the triaxial-acceleration sensors installed on the skilled practitioners when each of them did chest compressions; the acceleration (α_y) is of their left elbows in the *Y*

Table 1 Averaged values of chest compression depth measured by Microsoft Kinect, D_k and high-speed video camera, D_c.

Test subjects	A	B	C	D
AE: $\lvert D_k - D_c \rvert$ cm	1.3	0.9	1.7	0.7
RE: $D_k / D_c \times 100$ %	68.9	78.3	58.2	85.4

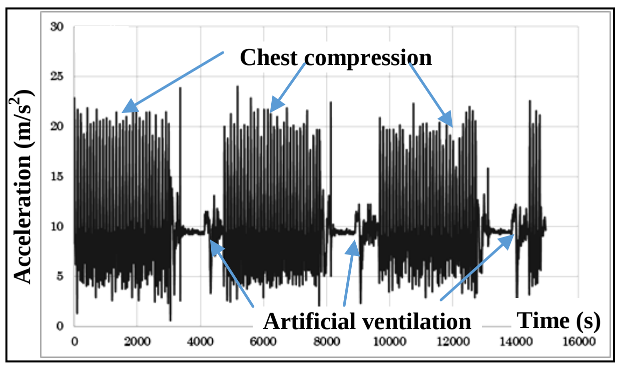


Fig. 9 Acceleration waveforms for left elbow measured by accelerometer installed on the skilled practitioners during chest compressions of CPR.

direction. The change in acceleration was observed to be almost at the same time as that for the CPR chest compressions. We observed the same tendency for other test subjects.

We recorded the waveforms or the data arrays of left-elbow displacement measurements made using the Microsoft Kinect sensor and the triaxial accelerometer (Y direction) during CPR chest compressions by each test subject. FFT analysis revealed a sharp peak in the displacement spectrum during CPR chest compressions measured by both the Kinect sensor (Fig. 10) and the accelerometer (Fig. 11). The new CPR guidelines [21, 22] call for 100 beats per minute (and refer to a memorable repeating drum pattern that is useful in particular for new practitioners learning CPR). This feature characterizes the chest compressions and is consistent with the new guidelines.

Table 2 lists the averaged maximum peak acceleration frequencies measured by the Microsoft Kinect sensor (Fig. 10) and the acceleration sensor (Fig. 11) in FFT analysis during CPR chest compressions. Thus, the peak spectrum frequencies both for the experienced and the inexperienced practitioners met the new standard, 100 beats-per-minute (and matched the memorable repeating drum pattern [22]).

Because temporal accuracy is evaluated on the basis of averaged values of peak-frequency difference, we looked at the temporal distance between the peak frequencies. As measured by Microsoft Kinect, the peak frequencies were almost the same as when we used the acceleration sensor in FFT analysis. Results related to the temporal accuracy show performance comparable between the systems. These features characterize the chest compressions and are consistent with the reports of other experimenters investigating chest compressions [21].

3.4 Discussion of Spatial and Temporal Accuracy

The goal of our study has been the analysis and evaluation of spatial and temporal accuracy of Kinect skeleton joints in tracking clinical features normally used by clinicians to evaluate practitioners' performance during CPR chest compressions. The clinical features separately measure the two fundamental characteristics of an action: the movement and the posture [7]. Results evaluating temporal accuracy show that the Kinect sensor can correctly measure timing characteristics of physical exercise, thus validating its use [8]. Regarding the spatial accuracy, the Kinect sensor is able to reproduce salient dynamic features in a manner comparable to those obtained from a high-speed video-camera system [9, 10].

The Microsoft Kinect sensor seems to ensure greater accuracy in motor tasks involving elbow joints during CPR chest compression. We also noted that a systematic error appears during maximum elbow

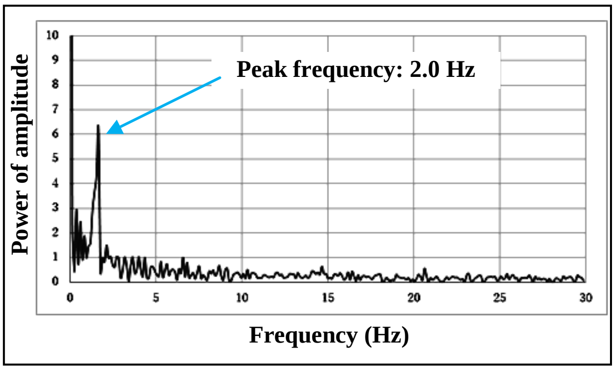


Fig. 10 FFT analysis of left elbow displacements measured by Microsoft Kinect during chest compressions of CPR.

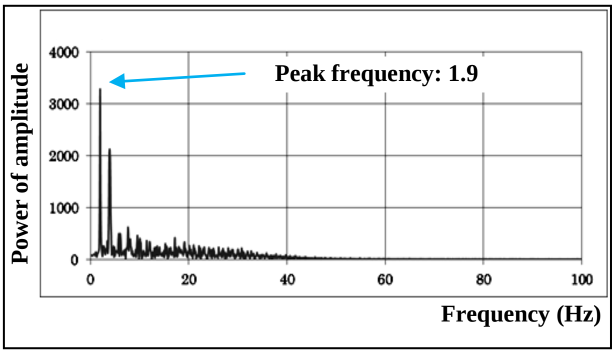


Fig. 11 FFT analysis of left elbow displacements measured by acceleration sensors during chest compressions of CPR.

Table 2 Averaged values of peak frequency measured by Microsoft Kinect, F_k and acceleration sensor, F_a in FFT analysis.

Test subjects	A	B	C	D
$F_k/F_a \times 100$ %	102.0	104.0	105.0	103.0

flexion by a new practitioner. This is probably due to wider translational and angular excursion by the new practitioner during the exercise, with a correspondingly larger measurement volume. In particular, during the maximum elbow flexion, some salient joints used to compute the clinical features seem to be estimated by Kinect with a systematic bias related to the image-based 3-D motion analysis.

A possible systematic error likely is not very significant for the continuous and overall temporal evaluation of the practitioners. Moreover, results in left-elbow displacement suggest that the magnitude of error is comparable during top and bottom oscillation, highlighting a vertical symmetry.

5. Conclusions

This study aimed at building a quantitative model of motion patterns by a comparatively simple method to evaluate the skills used in CPR and at developing an exercise-support system for new practitioners of CPR or for those who want to improve their movement techniques. As the first step in this study, we investigated whether objective evaluation could be performed by Microsoft Kinect in the same way as is done in image-based 3-D motion analysis.

Results show that the Microsoft Kinect sensor measurement enabled detailed motion information at installation points to be displayed in a short time. Although it became possible to match the standard index in the new CPR guidelines, which now is 100 beats-per-minute, and to relate it to a memorable repeating drum pattern, we were unable to extract objective characteristics of the chest-compression depth for experienced versus new CPR practitioners.

Although it was not possible to confirm the detailed motions of CPR chest compressions in the Microsoft Kinect sensor measurements using 3-D motion analysis and motion capture, we believe that an easily installed Microsoft Kinect sensor can quickly provide motion information as an evaluation tool. We also expect that this method will offer effective means for automatically evaluating the techniques of clinical practitioners in the future via computer.

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