UPPER LIMB JOINTS AND MOTIONS SAMPLING SYSTEM USING KINECT CAMERA

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Article History: Received 30 August 2018; Revised 22 November 2018; Accepted 19 December 2018

ABSTRACT: The needs of research on human posture and its joint-motion relationships are important. Providing a real-time postural measurement tool has attracted the attention of many human postural-related researchers. This study has developed and performed a validation analysis on a new innovative system for sampling and finding the angles of motions of each posture with its related joints using Kinect camera. The validation investigated the static and dynamic accuracy analyses by comparing to a Jamar goniometer and ErgoFellow system. The results showed that Mean Absolute Errors of Kinect in static and dynamic motions are 15.12% and 45.33% respectively. It is concluded that the postural measurement system developed by this study requires further improvements.

KEYWORDS: *Motion Analysis; Posture Estimation; Kinect Camera; Sampling*

1.0 INTRODUCTION

Work-related musculoskeletal disorders (WMSDs) are common injuries in a workplace environment. Awkward postures are one of the risk factors that greatly cause WMSDs. As stated in the annual report of Health and Safety Executive (HSE), in UK, 45% of disorders are from upper limbs or neck, 38% related to back, and 17% from joints of the lower limbs. It is highlighted that manual materials handling, repetitive motion in awkward or strenuous postures are the main causes of these disorders [1]. On that account, the need for studying human postures is crucial to reduce its risk factor. However, human posture by itself is a complicated system, since it consists of high movement degrees of freedom, with various body types and topologies. In addition to the complexity of the human posture, the environment plays a significant role in the identification and detection of human motion, due to effects such as occlusion and luminance [2-3]. Human motion is highly dependent on the human posture with its bones, joints and ligaments, and muscles with its tendons [4].

The interest in studying human motion appeared since ages, and perhaps it started to be a highly researched topic when the power of computers came into existence. Since the late 1970s, researchers have set their lives to find the most accurate unified mathematical models to define the human motion suitable with the limitation of the high speed intelligent electronic device processing. As such, it contributes and motivates to push the limits of technologies to achieve the dream of a real-time analysis of human motion [2]. In 2010, a new, innovative, cost-effective technology came into sight, with its ability to perform high speed human motion analysis. This technology combined the power of depth sensing with the two dimensional RGB camera to create a three dimensional spatial analysis of the scenes. This RGB-D camera is called Kinect and since its release, researchers have shown a significant interest to use this tool for solving the dream of a real-time human motion analysis [5-6]. Kinect provides a simplified tool to enable a software developer to track the skeletal motions related to their joints [7], and it has been widely used in previous studies. For example, in ergonomics studies, Kinect was used with various assessment tools especially with RULA Assessment tool [8-9]. Some research works did validation tests on Kinect with different models of experiments. Models were set into various aspects, such as: referenced validated tool comparison, Kinect accuracy behavior related to various positions and focused joint-motion relation. Abobakr et al. [10] conducted accuracy validation tests for 29 joint-motions using AlexNet algorithmic model. The overall average Mean Absolute Error (MAE) calculated was 4.67°, and the average Root Mean Square Error (RMSE) was 6.64°. Plantard et al. [11] measured the accuracy of Kinect for 13 joint-motions. The measured average angles error calculated ranged around 7.7° and 10°. Tarabini et al. [12] performed accuracy study comparison between Kinect, Notch Inertial Measurement Unit (IMU) system, and visual evaluation. The comparison was conducted on 12 joint-motions, and it was found that the RMS difference between Kinect and Notch system is lower than 10°. Marino et al. [13] used Goniometer as a gold standard to compare the various angles of joints-motions accuracy with Kinect. Despite the various validation studies on Kinect, none has considered the validation on both static and dynamic motion analyses.

The aim of this study was to develop an upper limb joint-motion sampling system using Kinect, by enabling the user to classify and choose the degree of motion readings, and save them into a database. Furthermore, a preliminary validation was conducted using a well-known instrumental mathematical equation to determine the error ratio. The accuracy percentage for each joint-motion position through two pilot studies in a specifically designed workflow process experiments was calculated. The percentage of accuracy is subjective to our software development, experimental process design, mathematical model, and the usage of the manual measurement tools.

2.0 DESIGN AND DEVELOPMENT

In the design and development of the joint-motion sampling system, C# .NET framework was used as the programming language for the development of this tool. The development stages of this research are as follow:

i. Design the process of using the Kinect joint-motion measurement tool and the software development.
ii. Design the standardized experimental procedures for static and dynamic motion analyses.
iii. Conduct preliminary experimental studies to analyze the accuracy of angle measurements of the developed system.

The design of an automated computerized joint-motion sampling measurement system started with identification of user requirements. This was carried out through a literature review which revealed that most users wanted a sampling system that is computerized, automated, user-friendly, and flexible. Neumann et al. [14] stated that sampling of posture with its related work is crucial, especially for assorted tasks. By quantifying the postural activity, more controlled and less biased judgments on human movements can be made. Karhu et al. [15] in their study in 1977, through questioning inspired future researchers to find ways to create an automated computerized system for posture and movement analysis. Chang et al. [16] and Wolf et al. [17] noted the importance of using computerized systems to quantify and classify human motions and postures. The developed system (Figure 1) was used in this study.

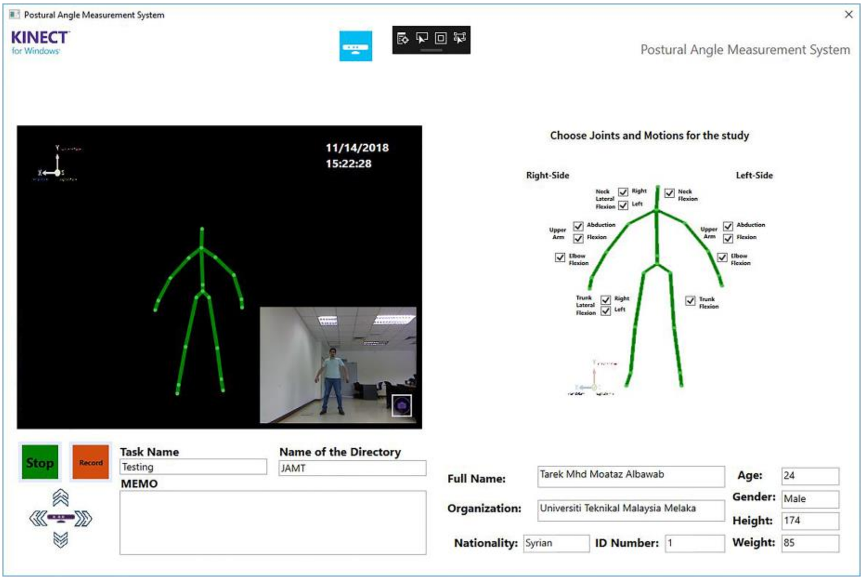


Figure 1: Kinect joint-motion angle measurement system interface

2.1 Process Design of using the Kinect Joint-Motion Measurement Tool and Software Development

The process design of the tool as shown in Figure 2 asks the user to start with registering the user's metadata by specifying the task name, and the directory to save the experimental data. Then, the user is asked to select joints and motions for the intended experiment as shown in Figure 3. The tool allows the user to choose three types of motions for four types of joints. The motions are: flexion/extension, lateral flexion, and abduction/adduction. The joints are: upper arm, elbow, trunk, and neck. Before the results of postural angles are recorded, the subject is asked to do a pre-test user checklist as described: (1) The subject is within 2.3 - 3.5 meters away from Kinect camera, (2) Only one subject is detected from Kinect camera, (3) The subject is in front-view of Kinect camera. The results will be recorded in the task name folder, in the directory path as specified previously.

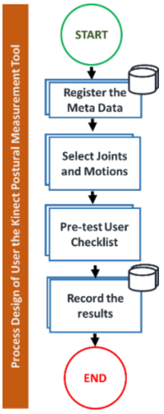


Figure 2: Process flowchart of the user interaction

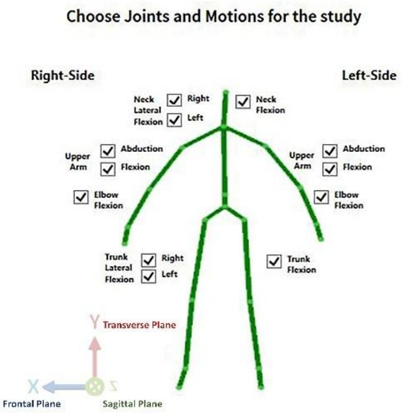


Figure 3: Joints and motions sampling selection from the software

The software development started with finding the most suitable algorithm to access the 3D vectors of joints in the skeletal tracking. Microsoft.Kinect and System.Windows.Media.Media3D namespaces were used to access the 3D vectors of the joints. Then, a calibration was made to define the angle between the joints and the Kinects' XYZ axes for various motions. This was followed by redefining the angles reading after general accuracy validation of the calibrated angles for several subjects. Figure 4 shows the process flow chart for the software development.

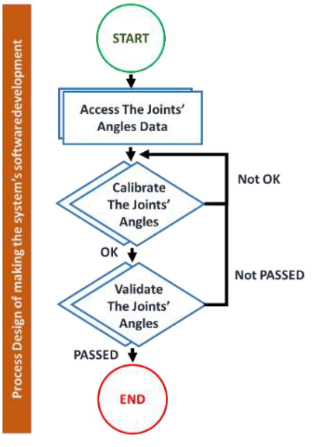


Figure 4: Process flowchart of the software development

2.2 Standard Operating Procedure Design for Static and Dynamic Analyses

The Standard Operating Procedure (SOP) for static postural validation was done through a comparison of a Kinect and a Jamar goniometer (Sammons Preston Roylan, USA). This research asked three subjects to perform three different poses for each different joint. Each pose has a different set of angles. Figure 5 shows the setup of the experiment. The goniometer was used to ensure the subject is in the specified postural angle, and to verify the recorded angles in the Kinect device. SOP design for dynamic postural validation was done with a comparison of a Kinect and a manual angles determination image analysis tool using ErgoFellow v3.0 software (FBF sistemas, Portugal). ErgoFellow software provides a tool for determining the angles in between two lines. The user in ErgoFellow set three points to determine and measure the angle of motion in the subject's recorded image. The dynamic postural study asked the user to perform a predefined work process, with four sequences, four motions and joints for three sample sized subjects. Figure 6 shows the Kinect dynamic postural results as compared to ErgoFellow software.

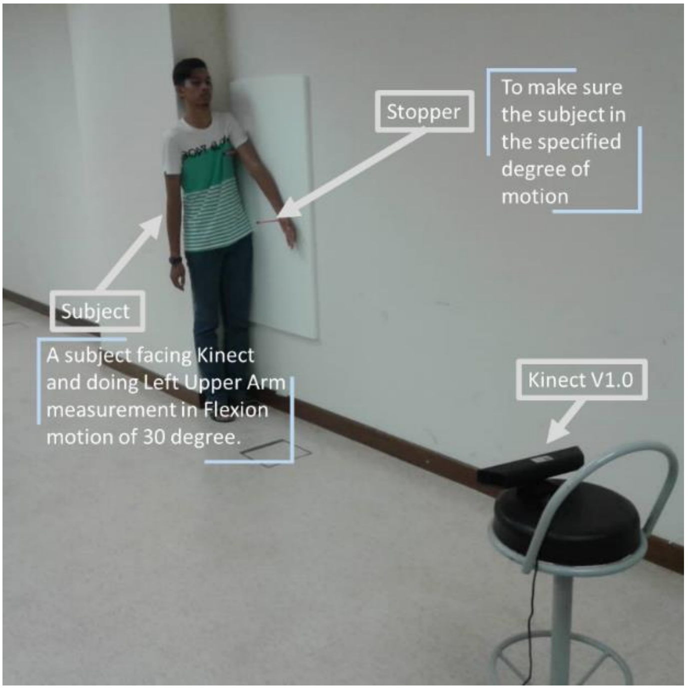


Figure 5: Setup experiment for static postural validation

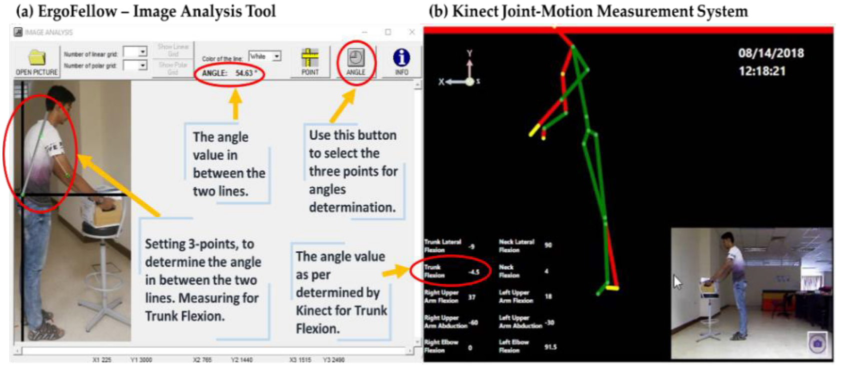


Figure 6: Dynamic postural validation study

2.3 Angles Accuracy Performance

In order to view the accuracy of the Kinect joint-motion measurement system, two pilot studies of validation were done; one as a static analysis, and another as a dynamic analysis. After getting the data of the pilot studies, the following mathematical model is used to view the overall percentage accuracy of the system:

$$\text{Relative Error} = \frac{|\text{Exact} - \text{Measured}|}{\text{Exact}} \tag{1}$$

$$\%\text{Accuracy} = (1 - \text{Relative Error}) \times 100 \tag{2}$$

$$\%\text{Overall Accuracy} = \frac{\sum \%\text{Accuracy}}{n} \tag{3}$$

Where,
Exact: is the Jamar goniometer value in static analysis, and the ErgoFellow value in the dynamic analysis.
Measured: is the Kinect joint-motion measurement of the studied motion.
n: is the sample size of the study.

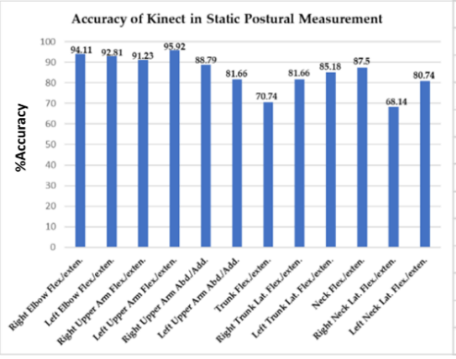
3.0 RESULTS AND DISCUSSION

The overall static motion analysis performance as seen in Figure 7, shows that trunk in flexion/extension motion, and neck in right lateral flexion motion are the least accurate. In addition, elbow and upper arm in right and left flexion/extension shows the best accuracy performances.

The overall dynamic motion analysis performance in Figure 8 shows that neck in flexion/extension dynamic motion is the least accurate in the study. Meanwhile, the right elbow in flexion/extension dynamic motion is the most accurate. Figure 9 shows the best motion analysis is when the subject in a standing position, while the least are in squatting and bending positions. Figure 10 and Table 1 show the overall accuracy performance of the system in static and dynamic motion analysis for upper arm, elbow, trunk, and neck in flexion/extension motion for a sample size of three subjects. It shows that the best performance is the elbow, followed by upper arm, neck, and trunk. In a static postural analysis, the accuracy of all joints' measurement is above 80%, except for trunk flexion/extension and neck lateral flexion. When the postures are in dynamic, this study managed to validate elbow, upper arm, trunk, and neck joints for flexion/extension motions. Adding both static and dynamic accuracy performances, this study observed that trunk and neck joint-motion measurement needs further improvements.

In this study, the overall Mean Absolute Errors (MAE) in static and dynamic validation were 15.12% and 45.33% respectively. The nearest validation experiment with this study is the work carried out by Marino et al. [13]. They used Kinect V2 in a static standing position imitating writing on a notebook. Their results showed better accuracy when measuring the trunk and upper arm. This might be due to the experimental design, workplace setup, software development, and version of the Kinect used. Meanwhile, studies by Abobakr et al. [10], [18] showed the MAE results were 4.4° to 7° in three implemented methodologies. Their enhanced accuracy is due to their focus on algorithmic comparisons while, this present study used a manual goniometer as a referenced validation tool, which may present some human errors due to its manual use.

As an alternative to the above-mentioned limitation, a new methodology can be proposed in joint-motion measurement using an RGB camera with intensive artificial intelligence techniques and engines, by accessing the joints of the skeletal tracking and defining their motions using methods as per discussed in these papers [19-21]. However, using such techniques needs high processing power computers to train the datasets, and to do the reasoning tasks on images in order to achieve a calibration-free, marker-free, occlusion-free, and real-time 2D image postural detection analysis.



Joints	100
Right Elbow Flex./exten.	94.111
Left Elbow Flex./exten.	92.815
Right Upper Arm Flex./exten.	91.235
Left Upper Arm Flex./exten.	95.926
Right Upper Arm Abd./Add.	88.796
Left Upper Arm Abd./Add.	81.667
Trunk Flex./exten.	70.741
Right Trunk Lat. Flex./exten.	81.667
Left Trunk Lat. Flex./exten.	85.185
Neck Flex./exten.	87.5
Right Neck Lat. Flex./exten.	68.148
Left Neck Lat. Flex./exten.	80.741

Figure 7: Overall accuracy performance of static postural analysis

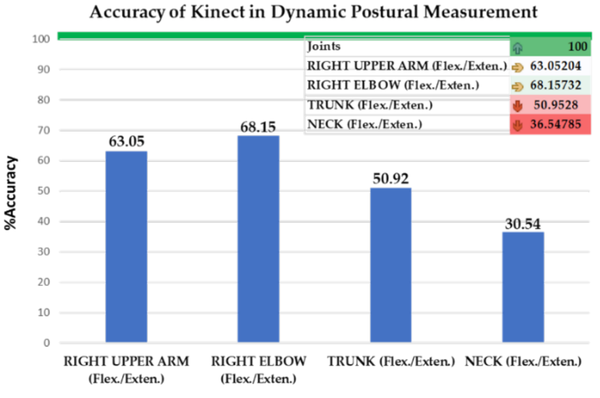


Figure 8: Overall accuracy performance of dynamic postural analysis

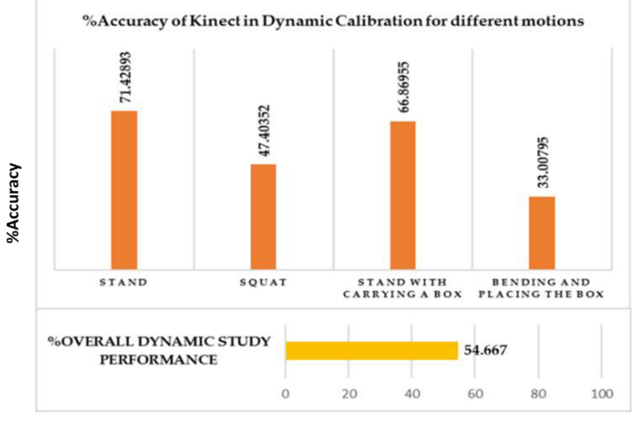


Figure 9: Overall accuracy performance of subject's position while performing dynamic postural analysis

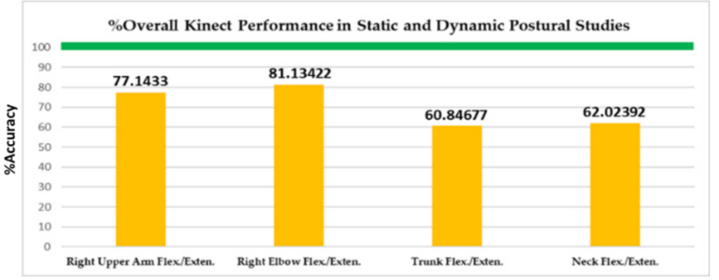


Figure 10: Overall accuracy performance of some joints in both static and dynamic postural analysis

Table 1: Some joint accuracy performances with respect to sample size

Joint	%Static Accuracy	%Dynamic Accuracy	%Overall Accuracy
Right Upper Arm	91.2345679	63.05203557	77.1433
Right Elbow	94.11111111	68.15732	81.13422
Trunk	70.74074074	50.9528	60.84677
Neck	87.5	36.54784622	62.02392

4.0 CONCLUSION

Measurement of human posture is a promising research topic. By finding the angle values of each joint in a certain motion can contribute knowledge to various areas of research such as ergonomics, sports analysis, medical studies, and multimedia. This study has contributed in two ways. The first is the development of joint-motion sampling automated system using a marker-free and users' calibration free Kinect device. The second contribution is a preliminary validation through two pilot studies in static and dynamic settings. The joint-motion sampling automated system developed by this study enables users to set the specified joint with its related motion, and register the results in the specified repository database. However, a preliminary validation through three subjects in static and dynamic settings showed that the Kinect has a big gap of inaccuracies when it is used as a joint-motion measurement tool. Therefore, further studies are needed to enhance the measurement accuracy and find the best tools or methodologies to develop an automated joint-motion sampling system.

ACKNOWLEDGMENTS

The researchers would like to thank the Fakulti Kejuruteraan Pembuatan, Universiti Teknikal Malaysia Melaka for funding this study under the University High Impact Short Term Grant (PJP/2017/FKP/H19/S01527).

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