Optimum Kinect Setup for Real-Time Ergonomic Risk Assessment on the Shop Floor

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Abstract. 3D motion sensors are useful for systematic and comprehensive data collection towards yielding 3D human motion data for real-time ergonomic analyses and possible automated interventions. Accurate sensor placement helps to ensure decreased measurement errors and increased depth resolutions. This paper presents the optimum Kinect placement setup for accurate data capture in real-time ergonomic evaluations. An application is developed which tracks human skeletal data to yield the best output for the optimal distance, height, and field of view of the sensor.

Keywords: Visual Gesture Builder; Discrete Gesture Basics; Work-Related Musculoskeletal Disorders.

1. Introduction

Work-related Musculoskeletal Disorders (WMSDs) are the most common cause of occupational ill-health on shop floors affecting the muscles, joints, tendons and other parts of the musculoskeletal system (Douphrate et. al., 2013; Grosse et. al., 2014). It affects manual labourers (Duy Nguyen et al., 2013), whose manual handling activities involve transporting or supporting of load by hand either by lifting, lowering, pulling, pushing, carrying, or moving, on the shop floor. These activities among operators if not well monitored can be detrimental to the worker's health (Martin et al., 2012). In the United Kingdom alone, 9.5 million working days were lost due to WMSDs in 2014/15. In a bid to curb this menace, researchers have developed many subjective and objective hardware and software ergonomic tools which evaluate the risks associated with manual handling on shop floors so as to reduce the risk of workers developing WMSDs. Correct application of these ergonomic risk assessment tools requires systematic and comprehensive approach to data collection (Okimoto & Teixeira, 2009; Diego-Mas & Alcaide-Marzal, 2014). Microsoft® Kinect is one hardware tool that can provide this as well as provide an opportunity for real-time feedback which is crucial for enabling instantaneous remedial actions (Plantard et. al., 2015). This paper seeks to establish the optimum setup of Kinect placement for more accurate data capture in real-time ergonomic evaluations involving lifting operations on the shop floor.

1.1 Background

There are different approaches to data collection for real-time ergonomic evaluations on the shop floor. These approaches range from observation methods that use video capture systems (Okimoto & Teixeira, 2009; Deros et. al., 2015; Hernan & Paola, 2013; Mukhopadhyay et. al., 2015) to direct intrusive methods which utilise wearable Marker-Based sensors (such as Accelerometers, Goniometers and Inclinometers) attached directly to the operator's body (Plantard et al., 2015; Dai & Ning, 2013).

In order to overcome the intrusive limitations posed by the use of Marker-Based sensors, low-cost depth cameras such as the Microsoft Kinect Sensor can be used. The Kinect Sensor provides an easy-to-use, calibration-free, and cheap alternative. It does not require markers and provides skeletal data that can be captured and analysed to obtain complex and dynamic human biomechanical motions in real time (Plantard et al., 2015; Dai & Ning, 2013). This is unlike ordinary video capture systems that though easy to use, are highly unreliable (Plantard et al., 2015) and do not give 3D information as well as accurate joint information of workers in congested workplaces (Peppoloni et. al., 2015).

The use of the Kinect sensor by many researchers, to capture human motion data for ergonomic analysis, has been found to give new and interesting insights into ergonomic studies (Bonnechère et al., 2014). Martin et al., (2012) integrated a static ergonomic model with the Kinect so as to capture and analyse data during lifting operations and this yielded accurate measurement of the recommended weight limit and strain on the worker's skeleton. It was also used to monitor and record the joint angles of workers during lifting operations so as to establish the correct and safe lifting techniques (Delpresto et al., 2013). Prakash Daphalapurkar (2012) used the sensor to capture the skeletal data of operators performing fastening operation on the shop floor for onward real time ergonomic evaluation using the RULA in Jack.

Despite the potential usefulness of Kinect for real time ergonomic evaluation, it has been established from literature that the accuracy of the data captured with the Kinect can be a function of its placement. For example, in Dutta (2012), the Kinect was placed at distances ranging from 1m to 3m from an operator at 54° and 39.1° horizontal and vertical field of views respectively. This placement yielded accurate skeletal data used for ergonomic evaluations. A similar approach was used by Bonnechere et al (2014) in which the Kinect was placed at distances of 1.5m, 2.0m and 2.5m from the operator. The results showed that a distance of 2.5m from the operator was the optimal Kinect placement. Banerjee et al., (2015) established that the accuracy of the depth values from the Kinect is sensitive to the distances of various objects within the field of view of the sensor on the shop floor. Their experiment revealed that if an object is too close or too far from the Kinect, the depth values are distorted. According to Khoshelham & Elberink (2012), the random error of depth measurement increases while the depth resolution decreases when the distance of the object from the Kinect is increased up to 5m. They therefore recommend that data be captured between distances of 1m to 3m from the Kinect.

The Kinect v1, which is currently incapable of detecting manual handling gestures, was used in the above mentioned research. In this paper, we make the following contributions:

(i) We make use of the machine learning technologies of Kinect v2 to train it in recognising a lift gesture. It is the plan that such a gesture will be used as a trigger to start skeletal kinematic data recording as well as to start real time ergonomic analysis of lift operations.

(ii) We carry out a comprehensive experiment to determine the optimal shop floor Kinect v2 sensor placement towards collecting accurate ergonomic data. This will ensure a greater confidence in the results of future ergonomic data analysis.

1.1.Problem Statement

In the past, some researchers who used the Kinect v1 as a data collection tool for ergonomic analysis used trial and error methods to establish the correct locations to place the sensor (Duy Nguyen et al., 2013; Martin et al., 2012). The aim of the experiment described in this paper is to establish the optimum placement for the Kinect v2 sensor towards acquiring accurate gesture measurements as well as its limitations at various operating distances and corresponding fields of view. This exercise will provide the information needed to optimally place fixed Kinect v2 sensors for continuous shop floor observation.

2. Methods

2.1.Experimental procedure

In this section, we discuss briefly how the tools in the Kinect for Windows® SDK 2.0 were used to train and detect a lifting gesture to trigger data recording for ergonomic analysis. Machine learning, which is the data processing ability of a computer to recognise complex patterns of data (Salle, 2015), and which involves using Kinect studio to record data clips (Lower, 2014), was used for gesture detection. The clips are then passed to the Visual Gesture Builder ((VGB) as found in the Kinect for Windows® SDK 2.0). Here the lift-gesture is trained using the Adaboost Trigger indicator; a machine learning algorithm (Nock & Nielsen, 2007), at point P_3 (90°) at a distance of 2m from the Kinect with the height of the sensor at 1.2m (see Figure 1).

After training the lift gesture, the .gbd file generated was utilised to develop an application by writing appropriate lines of codes in Discrete Gesture Basics which is another Kinect software tool for Windows® SDK 2.0. The developed application was then used to test the possible locations on the shop floor where the Kinect can be placed so as to acquire accurate data for ergonomic analysis.

2.2.Experimental setup

The components used in the experiment was the Kinect v2 sensor, a tripod stand, a laptop, tables, a simulated lifting object, meter rule, protractor, measuring tapes and software components which include the Kinect Studio, the VGB Preview and Discrete Gesture Basics. The software components are all found in the Kinect for Windows SDK 2.0.
In order to ascertain the optimum locations where the Kinect can be placed during data collection, measuring points (P_n) in the environment at varying distances (D_n) and orientation were set up as depicted in Table 1 and Figure 1.

Table 1 - Points of placement at various distances and angles

Parameters \ **Points**	$\boldsymbol{P_1}$	$\boldsymbol{P_2}$	$\boldsymbol{P_3}$	$\boldsymbol{P_4}$	$\boldsymbol{P_5}$
$\boldsymbol{D_1}$ **(m)**	2.0	2.0	2.0	2.0	2.0
$\boldsymbol{D_2}$ **(m)**	3.0	3.0	3.0	3.0	3.0
$\boldsymbol{D_3}$ **(m)**	4.0	4.0	4.0	4.0	4.0
	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$	$\boldsymbol{\theta_3}$	$\boldsymbol{\theta_4}$	$\boldsymbol{\theta_5}$
$\boldsymbol{\theta}$**(°)**	55	70	90	110	125

At each point, an operator lifts a load at a certain measured distance from the Kinect and at an angle which was maintained within the field of view of the Kinect v2 sensor, that is between 55° to 125° in the horizontal direction and 60° to the vertical.

Furthermore, for each of the points in Table 1, the Kinect v2 was adjusted to three heights; H_1= 1.2m, H_2= 1.7m and H_3= 2.2m. This enabled us to investigate the optimal height to place the Kinect on a shop floor.

At each distance D_n, specified angle placement θ_n and height H_n of the Kinect, an operator lifts a load. This load lift activity was recorded using the Kinect studio and analysed using the developed application in Discrete Gesture Basics

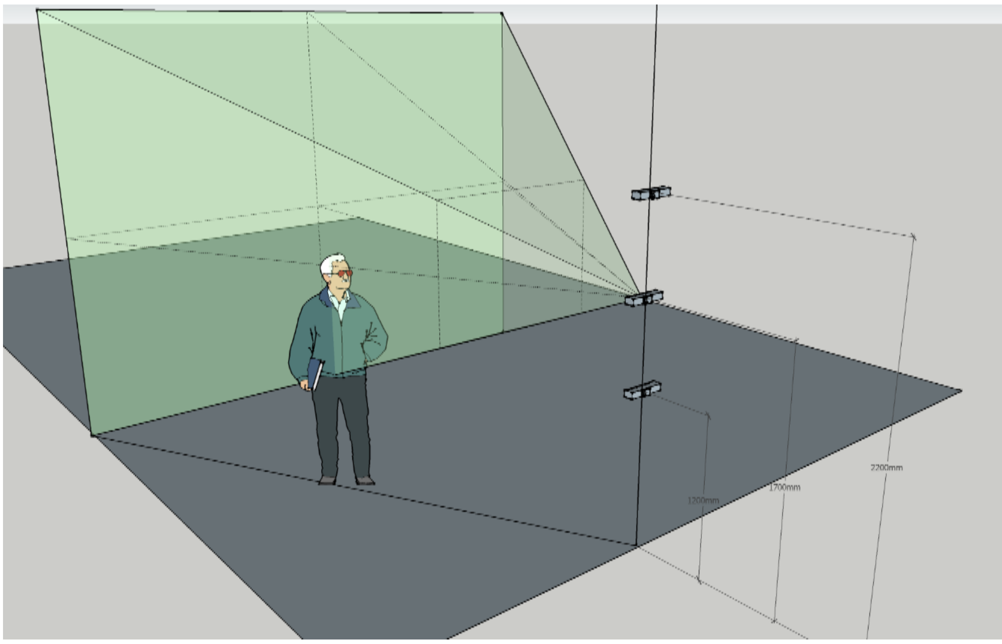

Figure 1 - Experimental setup for optimal Kinect v2 placement showing observation points, angles and distances (See Table 1).

3. Results

The aim of the experiment conducted in this research was to establish the optimum parameters of Kinect placement for more accurate data capture in real-time ergonomic evaluations involving lifting operations on the shop floor. The experiment started with training the lift gesture in Visual Gesture Builder. During the training, 32 lifting gestures were used. This resulted in 3079 labelled examples with an average RMS of 0.299 over 445 frames. Furthermore, an accuracy of 100% was obtained while the error was found to be 0%. After the lift gesture training, an application that can detect the lift gestures of operators on the shop floor was developed in Discrete Gesture Basics. The application could also display the confidence of the lift ranging from 0-1. The higher the confidence value at any point, the more the likelihood of the Kinect to track the operator at that point.

Figures 2 and 3 show the maximum confidence obtained at each of the location points for distances of 2m, 3m, and 4m, as well as the computed area of the confidences. The computed area of confidence was calculated by taking an integral of the confidence values under the confidence curve during the load lift operation. Table 2 summarises the overall result of the Kinect placement experiment as depicted by Figures 2 and 3. The terms ‘YES’, ‘NO’ or ‘PARTIALLY’ were used as follows: ‘YES’ means that the sensor can accurately track and give the correct gesture of the operator at the given location with confidence values above 0.5. 'NO' means that the sensor cannot track or 'see' the operator at that location. 'PARTIALLY' means that the sensor could track the gesture of the operator with confidence values below 0.5.

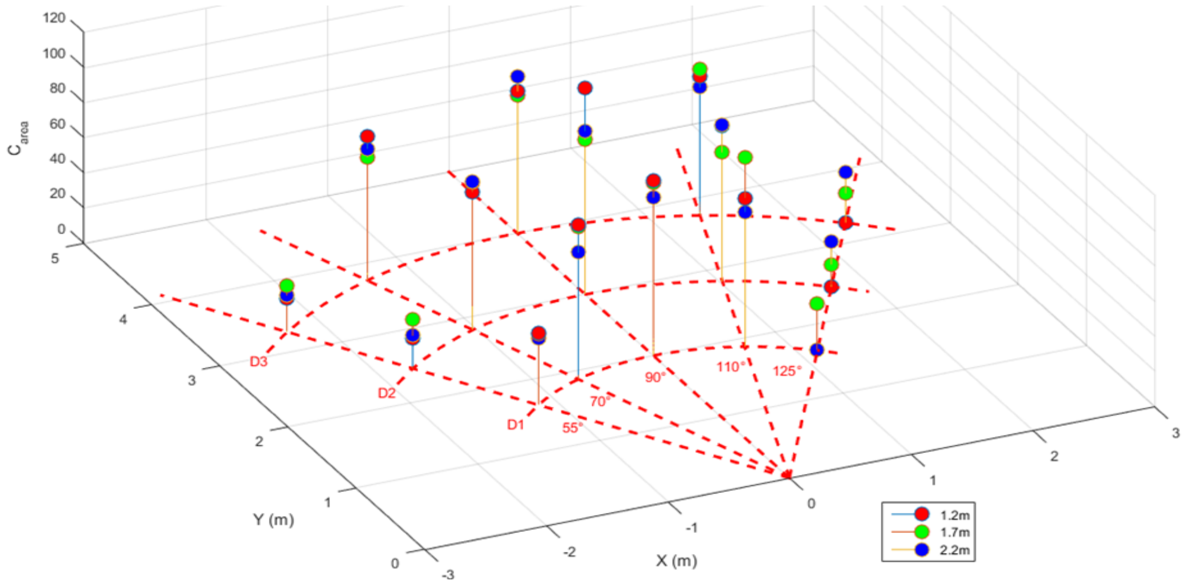

Figure 2 - Computed confidence area (C_{Area}) under the confidence curve within a time frame of 10 seconds.

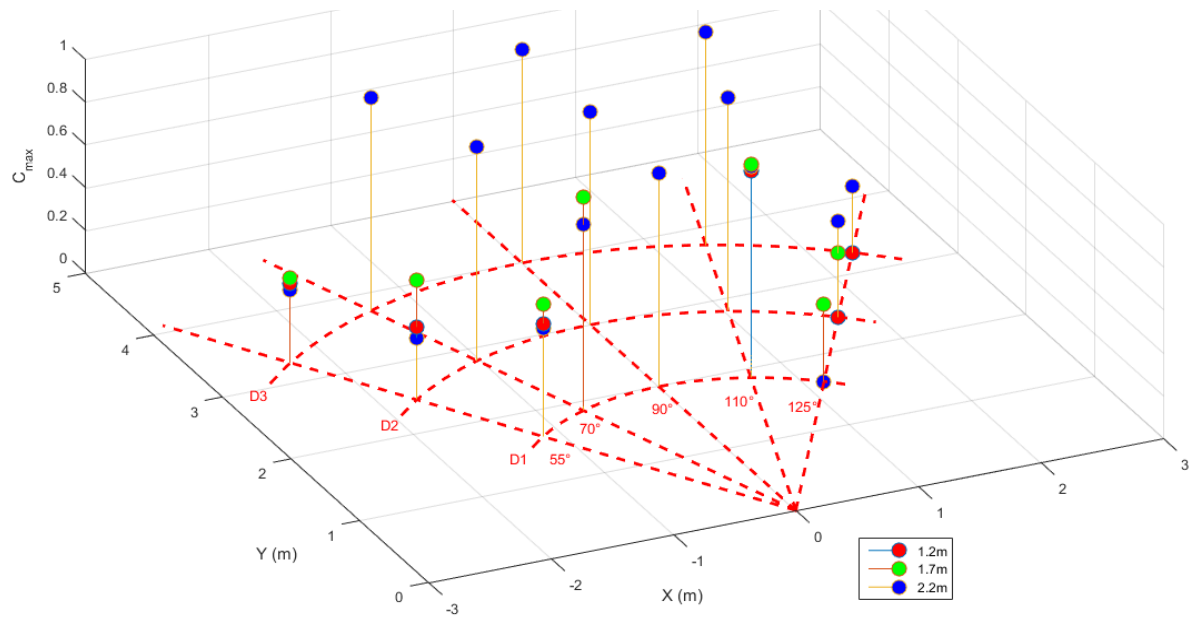

Figure 3 - Maximum confidence C_{max} of the confidence curve within a time frame of 10 seconds.

Table 2 - Summary of the Kinect v2 tracking performance at various points.

Points / Parameters	P_1	P_2	P_3	P_4	P_5
D_1, H_1	Partially	Yes	Yes	Yes	No
D_2, H_1	Partially	Yes	Yes	Yes	No
D_3, H_1	Partially	Yes	Yes	Yes	No
D_1, H_2	Partially	Yes	Yes	Yes	Partially
D_2, H_2	Partially	Yes	Yes	Yes	Partially
D_3, H_2	Partially	Yes	Yes	Yes	Partially
D_1, H_3	Partially	Yes	Yes	Yes	No
D_2, H_3	Partially	Yes	Yes	Yes	Partially
D_3, H_3	Partially	Yes	Yes	Yes	Partially

4. Discussion and Conclusion

Inaccurate placement of the Kinect on the shop floor during data collection for ergonomic evaluation has been found to lead to inaccurate depth values. Keeping the Kinect within the correct field of view and at correct distance and height from the operator is a key requirement in ensuring more accurate output. The results of training the lift gesture in the VGB showed a 100% accuracy and 0% error meaning that the training was perfect and the .gbd file and classifiers generated were accurate. This accurate training data was then utilised in developing the application in Discrete Gesture Basics, which is a tool in Kinect for windows SDK 2.0. The application can track up to 6 people simultaneously (Mgbemena et al., 2016).

Furthermore, Figures 2 and 3 show that at the two extremes of the field of view (that is at P_1 and P_5), the Kinect can only partially track humans as some of the skeletal information cannot be tracked. This is further justified by the low confidence values and low values of confidence area obtained at these points. However, within the field of view (that is at P_2, P_3 and P_4), the Kinect can track and generate accurate joint information of the operator. This is again justified by the high confidence values obtained at the distances of 2m to 4m and heights of Kinect varied at 1.2m, 1.7m and 2.2m. Moreover, the Kinect cannot track when it is maintained at a height of 1.2m, with the operator at any distance between 2m to 4m and at an angle 125° from the sensor. Also, it cannot track when it is at a height of 2.2m, with the operator at a distance of 2m and at an angle of 125°. Hence it is recommended that the Kinect should not be placed at these locations under any circumstances.

Therefore, it is the recommendation of the authors of this work that during data collection for ergonomic evaluation on the shop floor using the Kinect, the operator should stay in the envelope defined by points P_2, P_3, P_4 and at a distance of between 2m to 4m as specified in Table 2. This is because this is the envelope within which ergonomic data can be collected with highest confidence. Data obtained at the points represented by ‘Partially’, have low confidence and can therefore contain depth measurement errors.

In conclusion, this paper investigated the feasibility of detecting a manual shop floor activity using the Kinect v2 sensor so as to determine the optimal positions for Kinect v2 placement for more accurate data collection on the shop floor. These positions were found to be between 70° to 110°in the horizontal field of view of the Kinect v2 and within a 60° vertical field of view. Outside these angle ranges, the Kinect v2 can either partially track humans or not track at all.

The study provides ergonomists as well as other researchers with the optimal shop floor placements for the Kinect sensor during data capture for ergonomic risk assessment purposes. One limitation of the study however, is that the developed application is meant to be used on a Shop floor devoid of occlusions. It is part of a wider programme of work in which tools are developed for real-time evaluation and remedial action in industrial workplaces.

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