ACCURACY OF ESTIMATING HAND LOCATION DURING LIFTING USING FIVE WEARABLE MOTION SENSORS

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The purpose of this study was to assess two computation models for estimating the hand locations during lifting tasks using data from five inertial measurement units (IMUs) attached to five body segments. The first model computed the hand location with the IMU gyroscope data and the pre-defined ratios of body segment lengths. The second model used the same gyroscope information and all measured lengths of the body segments. The outcome measure of these models was the estimated hand location in 12 lifting zones defined by the ACGIH Threshold Limit Values (TLVs) for lifting. Motion data was collected with the wearable system and a laboratory-grade motion capture system on ten subjects that performed 12 two-handed lifting tasks representing the lifting zones. By including body segment measurements, the average accuracy of the model improved from 4 to 34%, suggesting that body segment information plays an important role in estimating the lifting zones.

INTRODUCTION

Work-related Musculoskeletal disorders (WMSDs) are one of the leading causes of lost workdays in industry and are associated with enormous economic costs (AAOS, 2008). In 2018, WMSDs accounted for 34% of all cases of nonfatal occupational injuries and illnesses requiring days away from work (BLS, 2018). To prevent WMSDs, accurate quantifications of risk factors are imperative (NAS, 1998; Bernard, 1997). High rates of WMSDs occur in occupations that require heavy work such as manual material handling. These tasks involve lifting that increases the risk of low back disorders (LBDs). Several risk assessment methods for LBDs are available, such as the American Conference of Governmental Industry Hygienists (ACGIH) Threshold Limit Values (TLV) for lifting. The ACGIH TLV for lifting was based on the most recent biomechanical, psychophysical, and epidemiological information (Marras & Hamrick, 2006). The ACGIH TLV for lifting considers physical risk factors such as the vertical location of the lift (V), horizontal location of the lift (H), lift frequency, lift duration (LD), and the weight of the load (ACGIH, 2005).

The ACGIH TLV for lifting may be considered a simplified version of the revised NIOSH lifting equation (RNLE) because of its tabulated format for determining the maximal allowable weight for lifting in various zones. For the RNLE and the ACGIH TLV for lifting, the H and V variables are sensitive factors for determining the maximal allowable weight for a given lift. However, taking measurements for the two variables in the field presents a challenge because of the need to interrupt work activity. With the advent of wearable inertial measurement unit (IMU) sensors, measuring these variables for the ACGIH TLV for lifting or the RNLE may become non-intrusive to workers, which may be a practical solution to the challenge in field data collection.

IMUs, which collect acceleration, gyroscope, and magnetometer data, are becoming very popular for recording information about whole-body postures for ergonomic risk assessments. The IMU sensors have been used to assess postural risks for WMSDs in various occupations (Peppoloni et al., 2016). Although the accuracy levels of IMU-based systems for ergonomic assessments have been previously studied (Barim et al., 2019; See et al., 2014; Aoki et al., 2016; Fang et al., 2018), only one has addressed the accuracy of IMU-based models for identifying the hand location (i.e., V and H of the ACGIH TLV for lifting) during lifting tasks (NAS, 1998; Bernard, 1997) .

We previously reported the accuracy of a five-IMU based wearable system for measuring V and H in terms of correlations between IMU data and data collected with a laboratory grade motion capture system (Lu et al., 2019; Barim et al., 2019). In this study, the objective was to evaluate the accuracy of the same wearable system for estimating the 12 lifting zones defined by the ACGIH TLV for lifting.

METHODOLOGY

Study Participants

Ten subjects (5 females and 5 males) from the National Institute for Occupational Safety and Health (NIOSH) in Cincinnati, Ohio, volunteered to participate in the study. The average (standard deviation) age of participants was 51.50 (9.83) years. Prior to data collection, written consent was obtained from the subjects in accordance with the NIOSH IRB approval study protocol. Colleagues who had musculoskeletal disorders or pain (now or in the past three months), were under age 18, were pregnant, or who were in the principal investigator's work unit were excluded.

Data Collection

Five wearable IMU sensors (Kinetic Inc.) and a motion capture system (OptiTrack and MotionMonitor® system, Innovative Sports Inc.) were used to collect the subjects' motion data. The placements of the sensors for the two body motion capture systems are described in our previous study (Barim et al., 2019).

During data collection, the IMU data were streamed continuously from 5 sensors to a data logger at a rate of 25 per second through Bluetooth connection. Prior to data collection, the internal clock of the sensor data logger was synchronized with the Universal Time Clock (UTC), which was used to synchronize the motion capture data.

Sensor data are fed into two major modules including the lifting detection module and the sensor fusion module that runs in parallel. The lifting detection module detects the occurrence of a lifting event with the timestamps of the beginning (BOL) and the ending (EOL) of the event. The sensor fusion module keeps track of the device orientations in real-time at 25 Hz and provides the angle of the sensor in three dimensions relative to the ground. The sensor fusion model is primarily used for correcting the gyroscope data for estimating the orientations of the body segments during a dynamic workplace environment.

Subjects performed 12 different symmetrical lifting tasks (Figure 1) on a sagittal plane with both motion sensors and markers attached. These ACGIH TLV lifting zones were used to define the H and V locations for the lifting tasks.

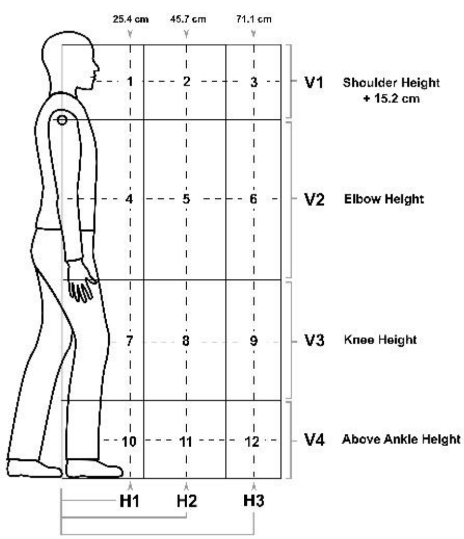

Figure 1. Initial lifting positions based on the ACGIH TLV for lifting (H1: near horizontal distance from the basket, H2: middle distance, H3: far distance, V1: vertical height shoulder level, V2: waist level, V3: knee level and V4: floor level). Source of figure: NIOSH

A light-weight grid with two handles was used as the simulated tote box for lifting. For each lifting task, subjects were asked to carry the grid from the starting point to the end point, a total distance of 3.3 M. To assure the location of the two hands were within the 12 lifting zones, the initial lifting positions were adjusted with respect to each subject's anthropometric measurements such as shoulder height, elbow height, knee height, and ankle height.

Before each lifting task, three distances of H were marked on the floor to specify the designated zones; H1: 25.4, H2: 45.7 and H3: 71 cm. These distances were measured from the midpoint between the two ankles to the midpoint between the two hands

Each lifting trial was repeated three times for a total of 36 lifting trials for each subject. These trials were randomly assigned in order to reduce learning effects.

Development of Models

Based on average anthropometric data, we used the forearm length as the base unit to estimate the lengths of other body segments. The resulting estimation is that the length of the upper arm (L_{UA}) is equal to the forearm (L_{FA}), whereas the length of the upper leg (L_{Thigh}) or the lower leg (L_{Calf}) is 1.2 times L_{FA}. The length of the spine (L_{back}) is estimated to be 1.4 times L_{FA} (Chaffin et al., 1999).

The second model was based on the actual measurement of the forearm length, upper arm length, back length, thigh length and calf length. With that information, the body length ratio model was able to compute V and H as actual distances for improving the accuracy of the model.

Body segment length information and the angular data (gyroscope data relative to the gravity) of four sensors on the back (θ_{Back}), thigh (θ_{Thigh}), forearm (θ_{FA}) and upper arm (θ_{UA}) were input into the trigonometry-based equations below to calculate V and H.

$$\boldsymbol{V = L_{back} \times \cos(\theta_{Back}) + L_{Thigh} \times \cos(\theta_{Thigh}) + L_{calf} - L_{UA} \times \cos(\theta_{UA}) - L_{FA} \times \cos(\theta_{FA})}$$

$$\boldsymbol{H = L_{UA} \times \sin(\theta_{UA}) + L_{FA} \times \sin(\theta_{FA}) + L_{Back} \times \sin(\theta_{Back}) - L_{thigh} \times \sin(\theta_{Thigh})}$$

The L_{calf} angle was not measured during lifts and was assumed to have little effect on the calculations for the H and V lifting risk variables. Therefore, this angle was ignored in the above equations

This body length ratio model (Figure 2) simplified the preparation process of using the IMU-based wearable sensor system for calculating V and H. The user needed only the measurement of the subject's forearm length to use the algorithm.

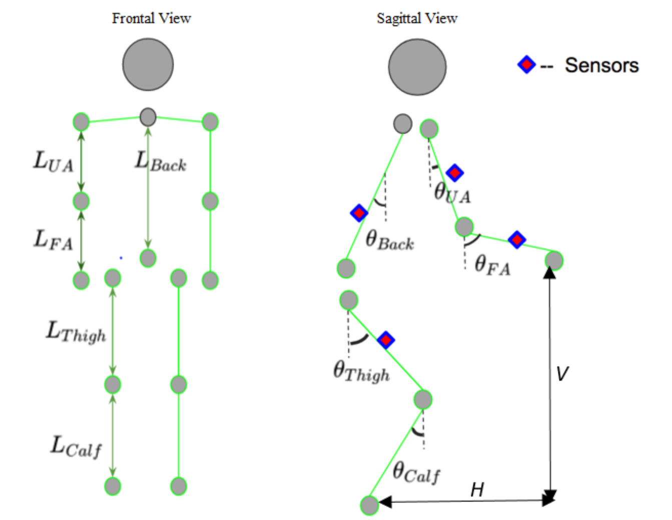

Figure 2. Body length ratio model and angular data of four sensors used for estimating H and V.

To improve the accuracy of the body length ratio model subjects' forearm length, upper arm length, back length, thigh length and calf length were all measured and input into the second (i.e., ratio + length) model. Source of figure: NIOSH

Accuracy Determination of Models

The accuracy of the models was assessed by comparing the hand locations estimated by the models with the lifting zones defined by the "gold standard" data collected by the laboratory motion capture system. Because (1) the initial vertical location of the lift was adjusted according to each subject's anthropometric information; and (2) subjects were unable to precisely place their foot position in the predefined locations in the horizontal zones at the beginning of the lift, the true lifting zones varied from trial to trial. Therefore, the ranges of the lifting zones defined by data collected with the motion capture system were used for assessing the accuracy of the wearable system. The analysis of the V and H information collected by the laboratory motion capture system revealed that V varied within four grouped vertical height ranges; V1:1.45-1.70 (m), V2:1-1.45 (m), V3:0.5-1 (m), V4: 0-0.5 (m). Similarly, H varied within each of the three grouped distances; H1:0-0.25 (m), H2:0.25-0.457 (m), H3:0.457-0.712 (m). These ranges were used for assessing three types of accuracy: (1) the accuracy of estimating H in the three H zones, (2) the accuracy of estimating V in the fours H zones, and (3) the accuracy of estimating the 12 lifting zones. For example, if the estimated hand location by the wearable system fell into zone 12, rather than 11 defined by laboratory motion capture data, the accuracy was zero. If the estimated V, H or zone matched the V, H and individual lift zones, respectively, defined by the laboratory motion capture system, the accuracy was 100%. The final accuracy measure was the average level of all the accuracy calculations across all trials. In other words, the final accuracy measure was the percentage of the correctly identified zone (V, H or individual lift) among all trials.

RESULTS

The Accuracy of V and H measurements were discussed in previous paper (Barim et al., 2019). The mean difference of V measurements of wearable (IMU data) versus motion monitor was 33 cm. The overall mean error for estimating H was 6.5 cm.

In this paper, to visualize the accuracy of hand locations estimated by the two models, the scatter plots of the estimated hand locations by the wearable system were presented in Figures 3 and 4 for the ratio and ratio + length model, respectively. The Y axis represents the vertical height (V) and the X axis represents the horizontal distance (H). Twelve gold standard lifting zones were defined by the lines V1-4 and H1-4.

Results of the accuracy analysis showed that the ratio model had a 37% accuracy of estimating H, a 14% accuracy of estimating V and a 4% of estimating each zone.

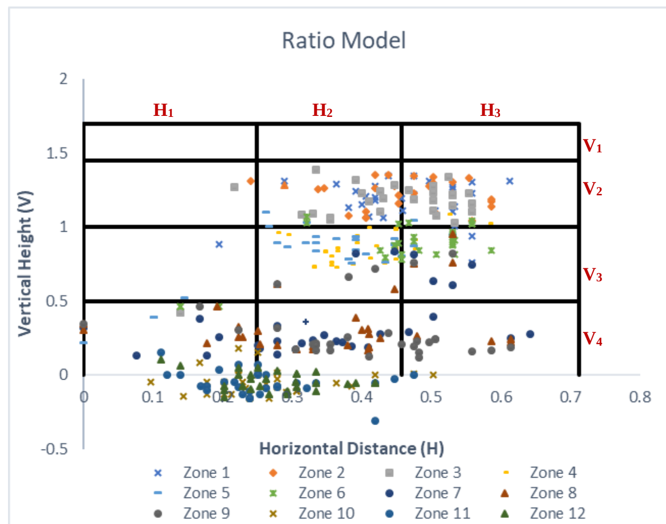

Figure 3. Zone Accuracy of Ratio Model

As shown in Figure 4, the accuracy of the ratio + length model improved for some of the measures. The vertical heights were estimated significantly better (a 61% accuracy vs. 14% accuracy for ratio model), whereas the accuracy of estimating horizontal distances decreased slightly to 34%. Overall, 28% of the lifting zones were estimated correctly.

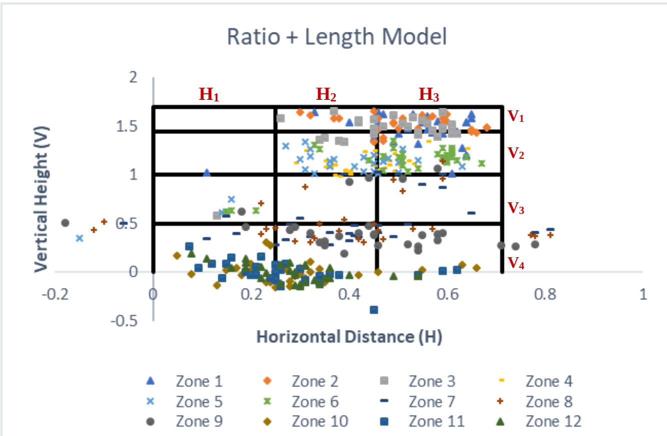

Figure 4. Zone Accuracy of Ratio + Length Model

DISCUSSION

This paper describes the evaluation of two computation models using five IMU wearable sensors data for estimating the lifting zones of the ACGIH TLV for lifting as a lifting risk factor. The differences in the overall accuracy levels for estimating each individual lift zone and V between the ratio and ratio + length models may be explained by the unrealistic representation of the predefined body segment ratios of the study subjects. The body segment ratios were based on the population means of the body segments to simplify data collection process for using the wearable system. The precise measurements of the body segment lengths improved the accuracy level from 4% to 34% for individual zones and 14% to 61% for V. The sensitivity of the accuracy improvement depended on the number of body segments used in computing V and H. Because one fewer body segment length was used for computing H than V, the accuracy of estimating H was not significantly different between the two models, as compared to V and individual zone. It should be noted that estimating H in one of the three horizontal zones by the wearable system using either ratio or ratio + length model presented no significantly difference between the system and chance (i.e., 33% or one of three zones).

Upon a closer examination of the video recordings of the lifting trials, we found that the rotations of the sensors on the arms may have caused inaccurate angular data. The X axis of the gyroscope data relative to the gravity direction was used for calculating V. To perform the lifting trials in V_1 zone, the subjects needed to pronate their arms, in particular the lower arms, resulting in biased projection of the gyroscope data on the sagittal plane. Consequently, the angular data of the sensors on the pronated arms might have caused inaccurate calculations of V. This finding is substantiated by the zero accuracy of estimating V in the V_1 zone (see Figures 3 and 4) for both models. This limitation may occur when movements of other body segments are not on the sagittal plane for using the two-dimensional computation models.

The accuracy calculation method used in this study did not adjust for the estimates that fell near the boundaries of the correct V, H and individual zones. In these cases, a zero accuracy was determined. However, the real difference between the correctly estimated zone and incorrectly estimated one might be very small (within a few centimeters in distance), as seen in Figures 3 and 4. This classification error may not be critical if one chooses to use the actual estimated distances for both V an H as the outcome measure. Our previous study has shown that the mean errors for using the ratio model to estimate V and H were 33 and 6.5 cm, respectively (Barim et al., 2019). These errors were significantly improved to 14 and 2.2 cm for V and H, respectively, if the measured body segment length information was used.

In Figure 3 and 4, the estimated hand locations were clustered in two regions for lifting trails above shoulder and below mid-shin heights. The two clusters of the estimated zones resulted from the inaccurately estimated hand locations in H_1 and H_2 for lifting trails in V_1 zone. Similarly, inaccurately estimated hand locations in H_2 and H_3 for lifting trails in V_4 zone caused data to cluster in the zones 10 or 11. The inaccurate estimations of the hand location was mostly likely caused by subjects' uneven lifting motion and missing laboratory-grade motion data. Because the missing motion data were estimated by proxy information near the missing points, errors in estimating the lifting zones increased. Upon a closer examination of the data for the two clusters, 7% of the lifting trials had uneven lifting motion and 8% of the motion data were missing.

Several limitations of this study are worth mentioning. First, the body length ratio model simplifies the data collection process at a cost of reduced accuracy. Second, with the additional input of the body segment length information, the improved average accuracy levels of H and V measurements may still not be adequate for measuring hand locations deviating from the middle horizontal zone, above the shoulder and below mid-shin heights. Third, the computation models for V and H cannot be applied to one-handed lifting tasks. Finally, the computation models were not designed for any lifting tasks involving asymmetry in the body segments out of the sagittal plane.

CONCLUSION

Using a limited number of wearable IMU sensors for measuring the hand locations of lifting tasks in relation to the body as a lifting risk factor may provide a practical solution to the challenge in the data collection for using RNLE or ACGIH TLV for lifting as ergonomic risk assessments. By including body segment measurements, the average accuracy of the zone prediction mode improved from 4 to 34%, suggesting that body segment information plays an important role in estimating the hand location of the ACGIH lifting zones. It is recommended that future research focuses on a different approach to estimating the hand location, such as machine learning approach or non-trigonometry-based estimations. Moreover, body motion data for manual lifting in the field may provide additional insight into the use of the wearable IMU sensor system.

Funding
The study was financially supported by intramural funding from the National Institute for Occupational Safety and Health (NIOSH). No conflict of interest is declared. This project was supported in part by an appointment to the Research Participation Program at the Centers for Disease Control and Prevention administered by the Oak Ridge Institute for Science and Education through an interagency agreement between the U.S. Department of Energy and the Centers for Disease Control and Prevention. The findings and conclusions in this article are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention.

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