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Ergonomic Risk Reduction: A Height-Adjustable Mesh Truck for Picking Activities Evaluated With A Depth Camera

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ABSTRACT

The correct assessment of ergonomic risks involved in picking activities is considered crucial step for avoiding musculoskeletal disorders in the workforce. In addition, the workplace and related tools should be designed to minimize those risks during daily activities. In this study, the researchers evaluated the benefits earned from introducing a height-adjustable mesh truck to facilitate and mitigate the risks in which operators are subjected. We evaluate the reported risks by exploring an Azure Kinect-based application which can semi-automatically assess the NIOSH index. We performed an experiment involving 20 volunteers who performed a total of 200 picking, statistically demonstrating the benefits that can be obtained with the introduction of a height-adjustable box.

Keywords: Depth cameras, Ergonomics, Kinect, Picking

INTRODUCTION

Recently the fourth Industrial Revolution took place, named Industry 4.0 (Liao et al., 2017). Under this revolution organizations, processes and the role of humans in Industrial production has changed (Neumann & Village, 2012). One of the key concepts of Industry 4.0 was the "full automation" principle (Coronado et al., 2022). However, even if the automation of manual activities improve the working conditions; there are many tasks where automation is not possible (Bortolini et al., 2017). In particular, the most labour intensive activity in logistics is order picking that usually represents 50% of warehouse costs (de Koster et al., 2007). Order picking is also critical from an ergonomic perspective since material handling is one of the most intensive activities from a physical point of view, this is due to high load weight, high repetitive and awkward body postures (Weisnera & Deusea, 2014). These characteristics can cause long-term musculoskeletal injuries to the worker therefore the occupational issue is called work related musculoskeletal disorders (WMSDs), those disorders negatively impact the workforce performance and health conditions. In fact, the U.S. Bureau of Labor Statistics found that 31.4% of the days away from work are imputable to WMSDs (BLS, 2017). WMSDs have also an economic impact that was estimated to be around $20 billion/year in US due to direct costs (Kang et al., 2014). Given this, there is major importance of delivering strategies to reduce WMDSs. Also, to reduce the ergonomic first risk exposure need to be assessed before implementing interventions which will be made to reduce the risk exposure (Vito Modesto Manghisi et al., 2017). To evaluate the ergonomic risks, three methods exists: self-reports, direct measurements and observational ones (Li & Buckle, 1999). The first method is highly affected by workers subjectivity (David, 2005) while direct ones are usually highly intrusive based on sensors mounted on workers body as well as their cost is high (Kowalski et al., 2012). The last class of methods is the most used in industrial practice and involve different methods among which we can find: Rapid Upper Limb Assessment (RULA) (Lynn & Corlett, 1993), Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), U.S. National Institute of Occupational Safety and Health (NIOSH) lifting equation (Snook & Ciriello, 1991), Strain Index (Moore & Garg, 1995), OVAKO Working posture Analysing System (OWAS) (Karhu et al., 1977) and the concise exposure index (OCRA) (Occhipinti, 1998). Among these methods the NIOSH lifting equation is considered the most used method to assess the risks involved in picking activities since it was developed in order to assess the risk of low-back disorders in repeated lifting operations (Waters et al., 1994). At the same time observational methods changed a lot in recent years. In fact, to reduce those major weaknesses, the increased duration of time needed to perform the video analysis, the low accuracy and high intra-and-inter-observer variability researchers started to integrate Motion Capture Technologies (MOCAP) in the ergonomic evaluation (Mgbemena et al., 2017). MOCAP can be classified in two different categories: sensor-based and optical side (Seghezzi et al., 2021). Sensor based systems are less used in industrial practice due to the users' discomfort sensation that is in contrast with a human-centered design (Coruzzolo et al., 2022). On the other hand optical system is not intrusive in the workspace or for the worker and represent a consolidate solution for ergonomic risk assessment (ERA) (Vito M. Manghisi et al., 2020). The most utilized cameras for the scope are Kinects: depth cameras that with a Convolutional Neural Network (CNN) embedded in the Microsoft SDK (Microsoft, 2021) provide a real time body segmentation. From its introduction, Kinects were utilized in various studies to conduct ERA. For example OWAS was calculated using Kinect v1 in (Diego-Mas & Alcaide-Marzal, 2014), RULA was semiautomatically calculated in (Vito Modesto Manghisi et al., 2017) using Kinect v2 as similarly done in (Plantard et al., 2017) and as done in (Coruzzolo et al., 2022) with Azure Kinect. For a full review of ERA with Kinects we refer to the work of Lunin & Glock, (2021). In this paper, we explore the new Azure Kinect to semi-automatically calculate NIOSH with and without the help of the height adjustable mesh truck. As far as our knowledge goes and as reported in (Lunin & Glock, 2021) this is the first work in which Azure Kinect is used for NIOSH evaluation. Some previous applications were developed based on

Kinect v1 and v2 that we follow for the development of AzKNIOSH. In particular, Delpresto et al. (Delpresto et al., 2013) developed a feedback system based on Kinect v1 that involved NIOSH, Spector et al. (Spector et al., 2014) developed an application which semi-automatically calculated NIOSH with Kinect v1 while Patrizi et al. (2016) compared Kinect v1 with a marker based high end method. Here we propose the introduction of a height adjustable mesh truck to reduce the ergonomic risk in picking activities demonstrating statistically its benefits from an ERA carried out with AzKNIOSH. The paper is structured as follows: Section 1 explains how the semi-automatic NIOSH evaluation is carried out with Azure Kinect using AzKNIOSH, Section 2 contains the experiment setting while Section 3 presents our results and Section 4 the conclusion and further research agenda.

AZKNIOSH

The NIOSH Lifting Equation analyse the ergonomic risk during manual load lifting providing the Recommended Weight Limit (RWL) (Waters et al., 1993). From the RWL we can calculate the Lifting Index (LI) that provides an insight into the level of risk while considering the lifted object that is obtained by dividing the RWL by the lifted object weight. The LI represents a measure of risk, higher the LI higher the risk involved in the lifting process. The levels of risk related to LI are reported in Table 1.

Table 1. Assignment of risk level based on Lifting Index (HSE (health and safety executive), 2014).

LI	Zone	Level of Risk
$\leq$ 0,85	Green	Negligible risk
0,86 - 1	Yellow	Medium risk
> 1	Red	High risk

METHOD

We implemented AzNIOSH on Python 3.8 with an application that semi automatically calculates the NIOSH Lifting Equation utilizing the Azure Kinect Body Tracking SDK (Microsoft, 2021). An algorithm based on CNN's is integrated in the depth camera to locate 32 joints in the 3D space.

Additional processing was required in order to calculate the NIOSH Lifting Equation multipliers:

- *Hands midpoint*: defined as the average of three-dimensional coordinates of the hands to calculate *Distance Multiplier (DM),* which is based on the vertical distance travelled during the lift.
- *Ankles midpoint*: defined as the average of three-dimensional coordinates of the ankles. The two midpoints are used for *Horizontal Multiplier (HM)* and *Vertical Multiplier (VM)*. As shown in Figure 1 on the right *HM* represents the horizontal distance between the object and the body (H) and *VM* is the vertical distance between the object and the floor (V).

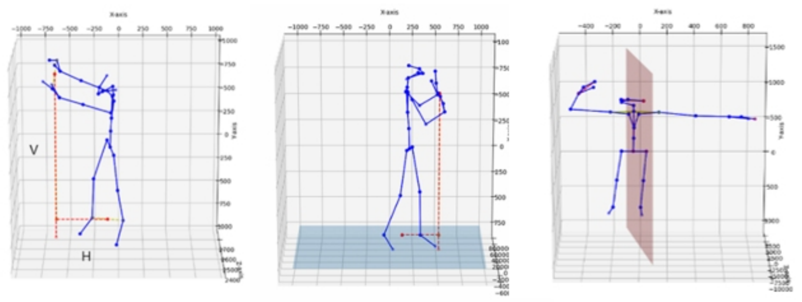

Figure 1: On the left: vertical (V) and horizontal (H) distances representation (left) and *floor plane* representation (right); in the middle floor plane is blue; on the right *sagittal plane* is shown in red.

- *Floor plane:* defined knowing a point belonging to it (the lowest joint, that corresponds to the foot coordinates in our experiment) and a vector defining its direction (parallel to the *z-axis)*. In Figure 1 in the middle is depicted in blue.
- *Asymmetric vector:* defined as the connection between the projection on *floor plane* of *hands midpoint* and *ankles midpoint*.
- *Sagittal plane:* found imposing its equation perpendicular to *shoulder vector* and imposing that contains the *trunk vector,* in Figure 1 on the right and illustrated in red.
- *Sagittal vector:* the intersection between the s*agittal plane and the floor plane*, used to find the *Asymmetric Multiplier (AM)*, based on the angle between *sagittal vector* and *asymmetric vector*.

- *Right/left hand tip vector*: defined as the vectors linking the joints *right/left hand* and *right/left hand tip*.
- *Right/left wrist vector:* defined as the vectors linking the joint *right/left hand* and *right/left wrist*.

Using *right/left hand tip vector* and *right/left wrist vector* researchers measured the fingers angle during lifting, this is used to calculate the *Coupling Multiplier (CM)*. To get final RWL it's necessary to provide as input the following parameters:

- Operator age and gender to calculate the *Load Constant (LC);*
- Lift frequency and duration to calculate *Frequency Multiplier (FM)*;
- Qualitative judgment of the grip and possible use of gloves contributing to *Coupling Multiplier*.
- The start and end of the lift i.e., the two frames where the lift starts and ends.

As given in the following equations, RWL is the result of multiplying all the factors then we can obtain LI.

$$
\begin{aligned}
RWL &= LC \cdot HM \cdot VM \cdot DM \cdot AM \cdot CM \cdot FM \\
LI &= \frac{L}{\mathrm{RWL}}
\end{aligned}
$$

The RWL can then be calculated for both the starting frame of the lift and for the stop frame, therefore the highest LI is the one that represents the lifting risk.

EXPERIMENT SETTING

For the video recording. An Azure Kinect was used with the following settings: Color mode On 720p, Depth mode On NFOV 2x2 binned, No depth delays, Frames per second (fps) 15, IMU ON, External Sync Standalone, Sync delay 0, Gain Auto. The Kinect was always placed at a height of 110 cm and at 150–200 cm from the subject. The experiment layout, shown from the Azure Kinect in Figure 2 and from a top graphical view in Figure 3 includes:

- Five shoeboxes, one on the top of the other, of size 40x30x30 cm, weight 0.50 kg. They were named from A to E, where "Shoebox A" was on the top and "Shoebox E" was the lowest one.
- A mesh truck of size 120x100x80 (h) cm, 67 cm usable height, where the shoeboxes were located. This is a height-adjustable mesh truck because its bottom part was moving, through mechanical non automated tools, to facilitate the lifting action as shown in Figure 2.
- A shelving of size 2000x500x1200 (h) cm where boxes were downloaded on the fourth shelf, 119 cm heigh, shown in Figure 2 and with a top view graphical representation in Figure 3.

Twenty volunteers participated in the experiment, lifting the shoeboxes from the mesh truck to the shelf. For each box two settings were analyzed: with the bottom part of the mesh truck fixed at 15 cm from the ground and the height-adjustable mesh truck with the moving bottom depending to the box vertical location. To observe the effect of the height-adjustable mesh truck on ergonomic risk assessment we populated a dataset with 200 videos. Volunteers' data summarized in the following: 7 female and 13 males; average age is 34.9 years old with a standard deviation of 11.1 (the youngest is 22 years old and the oldest is 54 years old); average height is 173.5 cm with a standard deviation of 8.3 (the taller is 190 cm height and the shortest is 160 cm). Other useful information to calculate semi-automatic NIOSH Lifting Equation are: the lift frequency was 7 lift/min; the lift duration was 8 hours; there was not optimal handle and volunteers didn't use gloves; we defined manually the start and stop frames for each lift. After the data

Figure 2: Lifting action with fixed mesh truck (left) and lifting action with height-adjustable mesh truck (right).

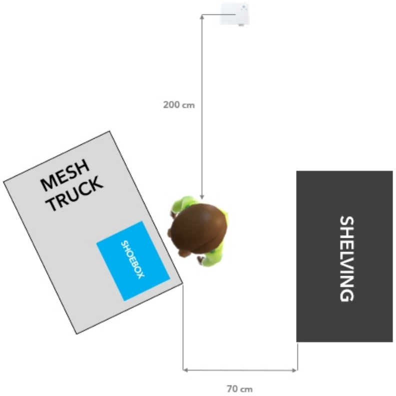

Figure 3: Experiment layout top view.

collection it was possible to compare the results of NIOSH Lifting Equation between the two lifting settings.

RESULTS

The 200 videos captured by Azure Kinect have been converted from *.mkv* files to *.json* file, this was done in order to give input for the semi-automatic NIOSH Lifting Equation carried out with AzKNIOSH. From the ergonomic risk assessment, we tested if there were some beneficial effects on the Lifting Index given by the height-adjustable mesh truck respect to the base one. To do that for each lifting we considered only the LI of the lift start frame, because the height-adjustable mesh truck affects just the lift from/to it and did not affect the disposal of the box in shelves. As shown in Figure 4, there is an overall average improvement of the Lifting Index of 17.1% among all volunteers with peak of 27%.

Analysing the results revealed a link between the percentage of improvement and the volunteer height, calculated correlation index confirms our supposition being equal to −0.356: shortest people have more difficulty to reach the shoeboxes, especially the lowest on the mesh truck, without the

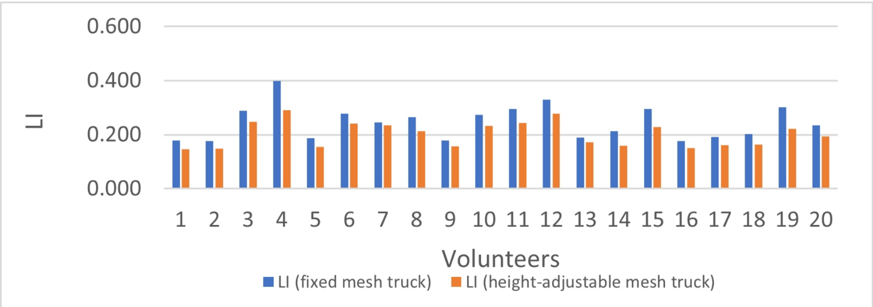

Figure 4: Comparison of lifting index calculated with fixed ad height-adjustable mesh truck for each volunteer.

height-adjustable platform; moving it up they can lift the load with a correct body posture and a better LI. Additionally, we found a significant percentage improvement for each box as reported in Figure 5. Correlation index calculated between shoebox position on the mesh truck and percentage improvement is 0.952, showing that the improvement is related to the boxes location on the mesh truck: Shoebox A is on the top of the pile, so the lift is not critical because is easily reachable; most percentage improvement is for Shoebox E because is the lowest one in the mesh truck and pick it up is very difficult, especially for short volunteers. To reach it volunteers must assume dangerous posture which involves a higher LI. By adjusting the mesh truck bottom part height is possible to take it on a height of 65 cm from the ground, leading to a better LI with an improvement of 27.9% for the lowest shoebox.

The researchers also carried out an ANOVA test on LI calculated for each lift to statistically validate that they belong to different populations varying with the usage of fixed mesh truck ground or the hight-adjustable one. First, we considered all the LI obtained with the fixed mesh truck ground and with the moving one independently on the shoebox and on the volunteer considered. We obtain a p-value of 1.27 e^{-06} that statistically confirm the reduction of LI obtainable with a mobile ground of the mesh truck. This difference is also visible in Figure 6 where the boxplot of this ANOVA was reported.

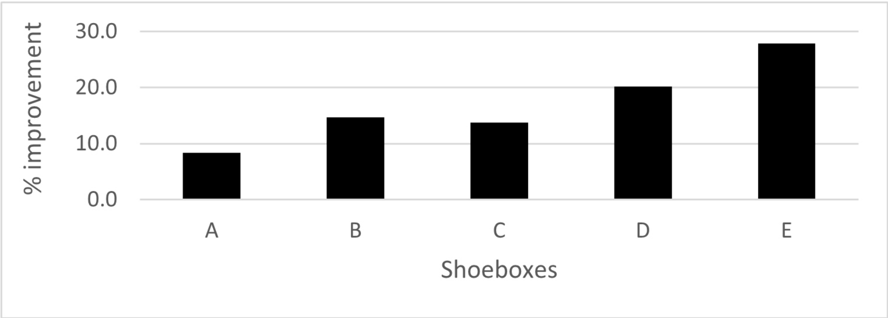

Figure 5: Percentage improvement between the two lifting settings for each shoebox.

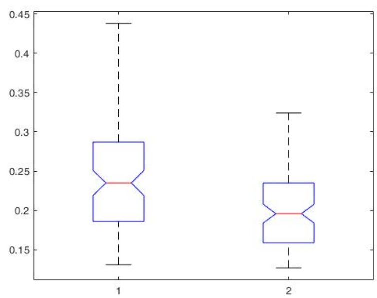

Figure 6: ANOVA boxplot for LI with fixed mesh truck (1) and LI with height-adjustable mesh truck (2).

Table 2. P-value for different shoeboxes.

SHOEBOX	A	B	C	D	E
p - value	0.3008	0.0568	0.0744	0.0107	0.0001

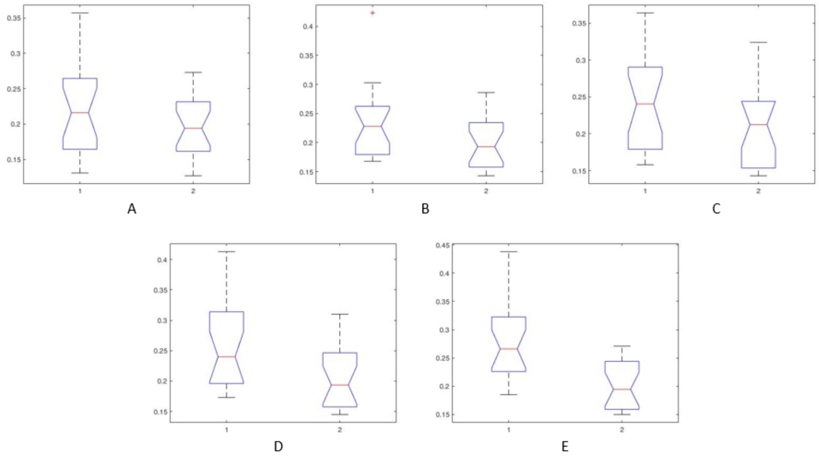

Figure 7: ANOVA boxplot for LI with fixed mesh truck (1) and LI with height-adjustable mesh truck (2), for each shoebox.

The lifts for shoebox type were grouped, then ANOVA test applied to the data. As shown in Table 2 for the three shoeboxes starting from the top (shoeboxes A, B and C), p-value proves there is no evidence to differentiate LI related to the two different settings. The p-value of the two lowest shoe boxes (shoeboxes D and E) is significant to accept the null hypothesis, so we can confirm that the usage of height-adjustable mesh truck affects the lifting of the lowest shoeboxes the most. Figure 7 illustrates the means of the two different groups for shoeboxes A, B and C are very closed, while the difference of the means between groups for shoeboxes D and E are significant different.

CONCLUSION

Applying strategies to reduce the ergonomic risk involved in picking activities is crucial since it is the most labor intensive and critical activities in warehouses (Weisnera & Deusea, 2014) (de Koster et al., 2007). In this work we evaluated the introduction of an heigh adjustable mesh truck to reduce the ergonomic risk of pickers. The evaluation was carried out with a new application based on Azure Kinect, AzKNIOSH, that semi-automatically calculates the said risk. In this study the researchers collect 200 videos from 20 different volunteers and we found an average risk reduction of 17.1% with peak of 27%. We also conduct an ANOVA on the two groups of LI, with and without the adjustable height mesh truck, that statistically demonstrates the benefits earnable from this tool. Extensions of this work would include both an economic analysis and the creation of "intelligent" mesh truck that is able to automatically adjust its height based on the quantity it contains.

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