Ergonomic risk assessment in lifting activities with Azure Kinect: an industrial case study

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Abstract: Work related musculoskeletal disorders (WMDs) are common in industrial activities and their impacts on society are not negligible. To reduce them recently some motion capture technologies (MOCAP) are applied to semi automatically calculate the ergonomic risk to which operators are subjected. In this paper we present an industrial case study where an application based on a depth camera, the new Azure Kinect, is exploited to semi-automatically calculate the ergonomic risk involved in picking activities. The case study took place in a warehouse and regarded three different activities. The semi-automatic evaluation of the ergonomic risk highlighted some criticalities on how picking activities are carried out. For this reason, some modifications of the activities are proposed and tested revealing a statistically significant ergonomic risk reduction.

Keywords: Ergonomic Risk; Depth camera; Warehouse; Picking Activities.

I. INTRODUCTION

These instructions are intended to provide the basic guidelines for preparing papers for the XXVII Summer School "Francesco Turco". Please use this document as a template to compose your manuscript or as an instruction set. Recently, a new industrial revolution was theorized named Industry 5.0 [1]. This revolution was conceptualized in order to cover the main drawbacks of Industry 4.0. Industry 4.0 which goals regard the achievement of higher efficiency and productivity of production system with high level of automation [2]. In addition, under Industry 4.0 the concept of smart manufacturing was introduced representing a interconnected production system able to achieve mass production using emerging technologies [3][4]. However, necessities to go beyond Industry 4.0 emerged in three different aspects: human centricity, the system resilience and environmental sustainability [5]. In particular, human centricity was neglected in Industry 4.0 where the full automation principle guided production choices [6]. But even if within the full automation principle many manual tasks have been automatize contributing in a continuous improvement of working conditions many tasks are still difficult to automate [7]. This is due to the fact that is still arduous for robots to learn soft skill and to acquire experience even if they are becoming more and more autonomous as well as collaborative [8]. For these reasons, most of the task performed by human operators are short and repetitive [9]. These task's characteristics favour Work Related Musculoskeletal Disorders (WMSDs) [10]. WMSDs have been defined as "All musculoskeletal disorders that are induced or aggravated by work and the circumstances of its performance" [11]. In Europe, has depicted in the 6th European Working Conditions Survey [12], repetitive hand and arm movements are widely diffused and reported by 3 workers over 5. A similar situation arises in the US where 31.4% of the days away from work are caused by WMSDs [13]. Obviously, WMSDs have an associated economic impact which was estimated to be about 20 million/year only for direct costs in the US [14]. While indirect costs of WMSDs can be up to five times the direct ones and comprehend for example the hiring and training of new workers [15]. In addition, the increasing aging in the workforce is putting pressure on the need to reduce WMSDs. In fact, in several developed countries aging workforce is predominant [16] requiring specific tools for the management of their comfort [17] and to reduce the ergonomic risk to which there are subjected. For the scope specific policies have to be applied trying to minimize the risks of WMSDs [18]. The initial phase of these policies regards the assessment of this risk exposure. Then, ergonomic interventions should be designed to reduce the assessed risk if present like workstation or task re-design [19]. Here in this paper, we propose both the assessment of risk exposure in picking activities in a real warehouse and the re-design of most critical task analysed. Specifically, for the risk assessment we applied a recent application based on the last depth camera of Microsoft, the Azure Kinect [20], named AzKNIOSH [21] to semiautomatically calculate the ergonomic risk in picking activities. In fact, recently many applications based on different sensors were proposed to automatize the ergonomic risk assessment [22] thanks to technology evolutions. This introduction took place to overcome the main drawbacks of classical ergonomic assessment. Three methods are available in literature to carry out the ergonomic assessment and are: self-reports, direct measurements, and observational methods [23]. The first class of methods are naturally affected by subjectivity [24] that is absent in direct methods where sensors are attached to the worker's body. At the same time, sensors have some drawback characteristics: are usually expensive and highly intrusive [25]. For these reason direct methods are not exploited in industrial environments but only in a design phase carried out in laboratory setting [26]. Observational methods are the most exploited by ergonomic practitioners [27]. Among these methods the most common are: Rapid Upper Limb Assessment (RULA) [28], Rapid Entire Body Assessment (REBA) [29], NIOSH lifting equation [30], Strain Index [31], Ovaco Working posture Analysing System (OWAS) [32] and the concise exposure index (OCRA) [33]. Despite their diffusion all these methods suffer of the same limitations: an ergonomic practitioner has to perform a time-consuming video analysis. Results of this video analysis have low accuracy and a high intra and inter observer variability. To overcame these limitations recently in literature many research integrated different MOCAP technologies to automatize and objectivize the ergonomic assessment. In this study, we utilized an application based on Azure Kinect to semi-automatically calculate the NIOSH lifting equation [34] in a real case study at a drug warehouse. The purpose was to determine the risk level of the analysed task using the Lifting Index (LI). LI measures the extent to which a task places excessive stress or strain on the human body, especially the back. The application takes into account factors such as the weight of the load and the distance it is lifted to calculate the LI value. This value serves as an indicator of the task's risk level: LI below 1 indicates a low risk level within acceptable ergonomic limits, while an LI greater than 1 suggests an existing risk, implying a higher likelihood of injury or strain. The paper is structured as follows: Section 2 provides a literature review on MOCAP technologies applied to ergonomic risk assessment, Section 3 presents our case study and related results while in Section 4 we stated our conclusions as well as further research agenda.

II. LITERATURE REVIEW

The growing interest on MOCAP applied to ergonomic assessment is demonstrated by the recent reviews published on the theme to which we refer for an in-depth analysis of the theme. In fact, in [35] authors proposed a systematic review of MOCAP applied to ergonomic assessment while in [36] authors focused on applications of Kinects to ergonomic assessment in material handling operations both in industrial case study and in laboratory setting. MOCAPs can be divided into sensors based and optical ones. As already stated sensors based applications are intrusive and exploited mainly in laboratory setting as reviewed in [37]. While optical ones are more easily applied in industrial environments even if suffer of occlusions problems [38]. Most exploited cameras to conduct ergonomic assessment are Kinects [36]. The first Kinect generation named Kinect V1 was firstly exploited in [39] for posture estimation in construction site. The first Kinect was also exploited in [40] to calculate OWAS with a good agreement with an ergonomic expert. Then, after the introduction of Kinect V2 which was able to truck more joints with an higher accuracy, researchers started using this new technology. In fact, in [22] authors proposed a semi-automatic calculation of the RULA index based on Kinect v2 finding an high agreement on 15 static posture between the proposed applications, an ergonomic practitioner, an optical system and a commercial software based on wearable sensors. Similarly, in [41] a substantial agreement was found between an ergonomic expert and RULA extracted from Kinect v2 data both in laboratory and real working environments. To lower occlusions in [9] authors proposed a Motion Analysis System (MAS) made up of four different Kinect v2. Occlusions problems that were also individuated in [42] where Kinect v2 was tested against an optical marked based system and wearable sensors. Results of their study shown the instability of RULA index provided by Kinect v2 in case of occlusions while they found that Kinect can be used in real working environment without several occlusion. Similar conclusions were found in [43] where authors found a fair to moderate agreement between the RULA score provided by Kinect V2 and by a MAS system made up of 8 Vicon cameras developed to overcame occlusions issue. The last Kinect generation, called Azure Kinect, was demonstrated to outperform the previous versions in different aspects: number of joints tracked, repeatability and in body segmentation when the narrow field-of-view depth mode (NFOV) is used [44]. However, Azure Kinect was applied is in [45] where authors compare the RULA score calculated with Azure Kinect data with an ergonomic expert and a machine vision algorithm based on simple RGB data finding a good agreement over the same 15 static postures proposed in [22]. At the same time, in [21] authors proposed a semiautomatic calculation of the NIOSH lifting equation based on the Azure Kinect. Here we exploited the same application named AzKNIOSH to calculate the ergonomic risk in picking activities carried out in a real industrial case study.

III. CASE STUDY

We tested AzKNIOSH, for semi-automatic calculation of NIOSH through Azure Kinect data, in an industrial environment. Specifically, the case study took place in a warehouse, where drugs are stored to be delivered to hospitals. Workplace characteristics are optimal to our scope because manual handling of loads accounts for most actions performed by operators. Three different activities were analysed with AzKNIOSH:

1. Picking for shipping rolls preparation.
2. Picking for material sorting.
3. Picking for automatic warehouse supply.

Azure Kinect settings during all the acquisitions were the following: color mode set On 720p; depth mode set On NFOV_2X2BINNED; no depth delays; 15 frames per second; IMU set ON; external sync Standalone; sync delay set 0; auto exposure and auto gain.

A. Activity 1: picking for shipping rolls preparation.

In the first activity, picking for shipping rolls preparations, an operator picks up from the rollers a box to place it on the shipping pallet. This task has the following characteristic: 2 operators on each shift; each shift duration is of 8 hours; the average weight of each box is of 4 kg; box dimension is 55 x 38 x 25 cm; 6 lifts are analysed, one for each level created on the pallet; boxes are picked up from a height of 50 cm and 110 cm from the ground.

Each pallet contains 24 boxes, placed on 6 height levels, as shown in Figure 1 while Figure 2 show an example of the analysed postures for the first activity.

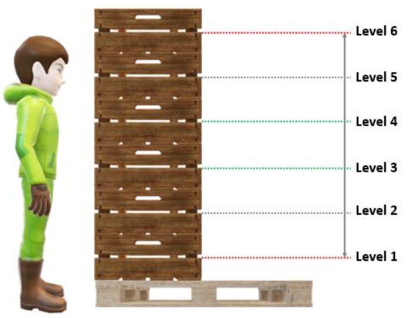

Figure 1. Graphical representation of the boxes on the pallet

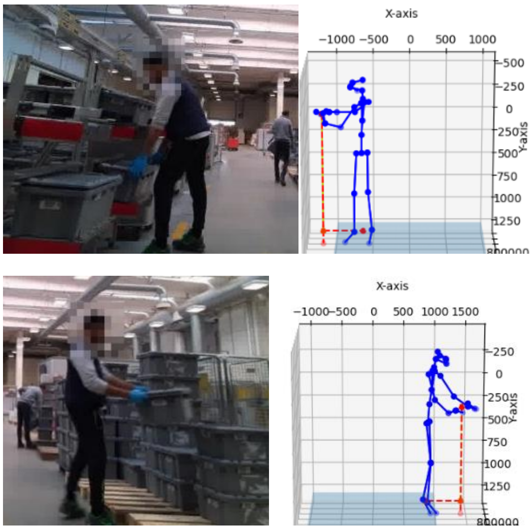

Figure 2. Graphical representation of the boxes on the pallet

Through AzKNIOSH we obtained Lifting Index for the frame when the lift starts and the frame when the lift stops. These frames of interest were manually identified by watching the acquisitions. We obtained two LI for each lift, but AzKNIOSH chooses the maximum LI to classify the risk of the picking. The average LI is 1.90, with a maximum of 2.22 and a minimum of 1.51, as shown in Figure 3 where red lines shown risk level limits: activity is considered risky with LI>1 and there are different risk levels according to the LI. Lifting performed during activity 1 are in the first and second level.

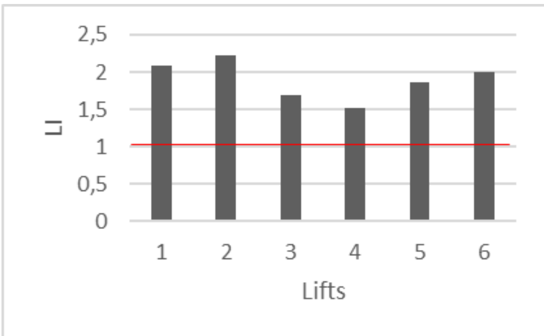

Figure 3. LI in first picking activity

B. Activity 2: picking for material sorting

Second activity is composed of three sub tasks:

1. Picking up an empty box to place it at a comfortable height.
2. Picking up materials to refill boxes.
3. Picking of box to place it on a pallet.

Sub tasks sequencing is shown in Fig.4.

Figure 4. Graphic representation of sub-tasks.

This activity has the following characteristic: 2 operators on each shift; each shift duration is of 8 hours; the average weight of each box is of 6 kg; box dimension is 59 x 40 x 27 cm; 6 lifts are analyzed, one for each level created on the pallet; boxes are picked up from a height of 80 cm from the ground. We analyzed 16 sub-tasks, and we obtained the following results: the average LI is 0.71 with a maximum of 1.39 and a minimum of 0.17.

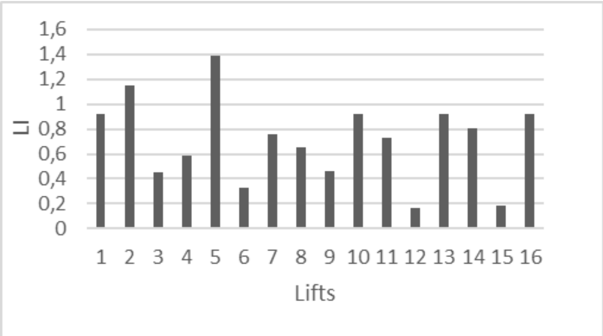

Figure 5. Lifting Index calculated for activity 2.

C. Activity 3: Picking for automatic warehouse supply.

Third activity scope is to supply automatic warehouse with boxes refilled during activity 2. An operator picks up boxes from different levels on the pallet, as shown in Figure 1, and leaves them on the roller.

This activity has the following characteristic: 2 operators on each shift; each shift duration is of 8 hours; the average weight of each box is of 6 kg; box dimension is 59 x 40 x 27 cm; 6 lifts are analysed, one for each level created on the pallet; boxes are picked up from a height of 100 cm from the ground.

During the testing we proposed an improvement solution to make more comfortable the placement of the box on the roller. An industrial trolley was placed near the roller to extend it facilizing the task. In Figure 6 the activity 3 is shown. In Figure 7 the comparison with the improved solution is shown.

Figure 6. Analyzed postures of the operators during picking automatic warehouse supply, an example.

Figure 7. Analyzed postures of the operators during picking automatic warehouse supply, an example.

There is an overall average improvement of the Lifting Index of 22% if the task is performed with the industrial trolley. We also carried out an ANOVA test on LI calculated for two configurations to statistically validate their difference. We obtained a p-value of 0.02 that statistically confirms the reduction of LI obtained with the usage of an industrial trolley.

D. Activity 3: Picking for automatic warehouse supply.

The implementation of semi-automatic ergonomic risk assessment through AzKNIOSH tool in industrial environment produced the following results:

1. Activity 1 is the riskiest activity, with a maximum LI of 2.22. Each analyzed lift in this task is classified as risky.

2. Activity 2 Lifting Index has only 2 risky peaks with a maximum of 1.39.

3. Activity 3 is a safe task with or without the usage of industrial trolley that undoubtedly facilitate the action.

Here we propose some comprehensive considerations of the activities. The first one is related to the horizontal distance from the operator to the box location on pallets: when the box is located on the pallet in Position 2 (Figure 8) it could be too far for the operator who must lean forward, increasing considerably the risk. In fact, we demonstrated it with ANOVA test where 18 lifts were analyzed: in 9 lifts box is picked up from Position 1 and in 9 lifts box is picked up from Position 2. We applied the ANOVA test on these two groups from which we obtained a p-value of 2,78 E-06. So, we can affirm that the risk is higher when the box is in Position 2. Specifically, we calculated the average of LI for the two different populations considered for ANOVA test, and we obtained an LI greater than 43% if box is in Position 2.

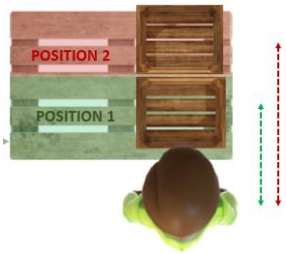

Figure 8. Graphical representation of the positioning of the boxes on the pallet.

Each pallet contains 24 boxes, with 6 vertical levels. This means that the height from which boxes are picked has a wide range. Specifically, the maximum vertical level is 170 cm from the ground, the minimum one is 45 cm from the ground. Our analysis confirms that Level 1 and Level 6 (Figure 1) can be inconvenient and hazardous to reach.

To make activity safe and comfortable for the operators, we propose two solutions:

1. Greater spacing between pallets to allow operators to get as close as possible to boxes locations. In this way operators can always pick the boxes from Position 1. Figure 9 shows the proposed layout.

2. Overlapping two pallets to elevate the lowest box in Level 1 and discard using Level 6. In this way, boxes vertical distances from the ground will be safer. A graphical representation of the proposed solution is shown in Figure 10.

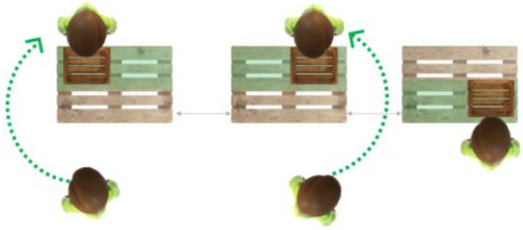

Figure 9. Graphical representation of the positioning of the pallets in the new proposed layout.

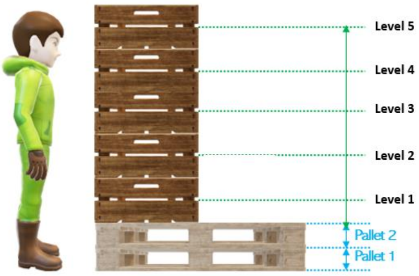

Figure 10. Graphical representation of the positioning of the boxes on the pallet with new layout

IV. Conclusion

In this paper we proposed a case study of an application based on the new Azure Kinect to semi-automatically assess the risk involved in picking activities through the calculation of the NIOSH lifting equation. The case study regards a drug warehouse where picking activities are prevalent. We analysed three different activities and one of them showed a critical risk for each lift taken under consideration. To reduce the said risk, we proposed three modifications statistically testing two of them to demonstrate their advantages finding an average risk reduction of 22% and of 43%. Future research in this direction can include a complete re-design of the three activities carried out in laboratory environments with the help of wearable sensors.

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