Applied Ergonomics xxx (2017) 1–11

Contents lists available at ScienceDirect

Applied Ergonomics

journal homepage: www.elsevier.com/locate/apergo

Real time RULA assessment using Kinect v2 sensor

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A R T I C L E I N F O

Article history:
Received 15 June 2016
Received in revised form
16 December 2016
Accepted 22 February 2017
Available online xxx

Keywords:
Kinect v2
RULA
Ergonomics

A B S T R A C T

The evaluation of the exposure to risk factors in workplaces and their subsequent redesign represent one of the practices to lessen the frequency of work-related musculoskeletal disorders. In this paper we present K2RULA, a semi-automatic RULA evaluation software based on the Microsoft Kinect v2 depth camera, aimed at detecting awkward postures in real time, but also in off-line analysis. We validated our tool with two experiments. In the first one, we compared the K2RULA grand-scores with those obtained with a reference optical motion capture system and we found a statistical perfect match according to the Landis and Koch scale (proportion agreement index = 0.97, k = 0.87). In the second experiment, we evaluated the agreement of the grand-scores returned by the proposed application with those obtained by a RULA expert rater, finding again a statistical perfect match (proportion agreement index = 0.96, k = 0.84), whereas a commercial software based on Kinect v1 sensor showed a lower agreement (proportion agreement index = 0.82, k = 0.34).

1. Introduction

Despite the steady improvement in working conditions, according to the Sixth European Working Conditions Survey (Eurofound, 2015), exposure to repetitive arm movements and tiring positions still remains a common issue. Taking into account worker's health and also welfare costs, it is mandatory to apply policies aimed at minimizing risks belonging to the work-related musculoskeletal disorders (WMSDs). WMSDs include “all musculoskeletal disorders that are induced or aggravated by work and the circumstances of its performance” (WHO and others, 2003). The best applicable practice to prevent WMSDs consists in the evaluation of the exposure to risk factors in the workplace and in planning an eventual ergonomic intervention as the workplace redesign.

Many methods have been developed with this goal. They can be classified into three groups: i) self-report; ii) direct measurement, and iii) observational methods (Li and Buckle, 1999). Self-reports methods suffer from non-objective factors and are affected by intrinsic limits of subjective evaluations (Balogh et al., 2004; David, 2005). Direct methods use data from sensors attached to the worker's body, but they are typically more expensive, intrusive, and time-consuming (Kowalski et al., 2012; Xu et al., 2015). Observational methods, which are widely applied in industry, consist of direct observation of the worker during his work shift. A detailed review of the most common observational methods can be found in (Roman-Liu, 2014) where OWAS, revised NIOSH, RULA, OCRA, REBA, LUBA, and EAWS are compared. In industrial practice, posture data are collected through subjective observation or estimation of body-joint angles in pictures/videos.

Supplementary video related to this article can be found at http://dx.doi.org/10.1016/j.apergo.2017.02.015.

These methods have the main disadvantage to require a field expert who performs a time consuming analysis of the postures. The introduction of low-cost and calibration-free depth cameras, such as the Microsoft Kinect v1 sensor, provided easy-to-use devices to collect data at high frequencies, and suggested a semi-automatic approach to observational methods. Several authors studied the accuracy of kinematic data provided by the Kinect v1 device in various application domains (Clark et al., 2012, 2013; Dutta, 2012; Bonnechere et al., 2014; Xu et al., 2015). The results showed that Kinect v1 is accurate enough to capture human skeletons in a workplace environment. The accuracy and robustness of the provided joint positions (skeleton tracking) are promising for applications that require to fill in an ergonomic assessment grid (Diego-Mas and Alcaide-Marzal, 2014; Plantard et al., 2015). Patrizi et al. (2015) compared a marker-based optical motion capture system with a Kinect v1 for the assessment of the human posture

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http://dx.doi.org/10.1016/j.apergo.2017.02.015

during working tasks and the recommended weight limit in the NIOSH lifting equation. Two other works exploited Kinect v1 to compute an ergonomic score based on the EAWS method (Nguyen et al., 2014; Kruger and Nguyen, 2015).

Observational methods like OWAS, NIOSH, OCRA, and EAWS, even if supported by depth cameras user data, still require a heavy intervention by a field expert to estimate the required parameters (e.g. forces, loads, static/repetitive muscular activity etc.). The ISO standard 11228-3:2007(E) (ISO, 2007) suggests the use of a simplified method in the early stage of the analysis and, if critical conditions are detected, provides the OCRA method to be applied for additional investigation. Among the simplified methods for rapid analysis of mainly static tasks, the RULA, acronym of Rapid Upper Limb Assessment, is one of the most popular (McAtamney and Nigel Corlett, 1993). The main weakness of RULA is related to the inter-rater reliability. Robertson et al. (2009) found just “fair” inter-rater reliability of the RULA grand-score (ICC<0.5) among four trained raters. Dockrell et al. (2012) proposed an investigation of the reliability of RULA that demonstrated higher intra-rater reliability than inter-rater reliability implying that serial assessments would be more consistent if carried out by the same person. Bao et al. (2009) showed that, if a “fixed-width” categorization strategy is used when classifying the angles between body segments, the inter-rater reliability grows with the amplitude of the width. Moreover, larger body parts as shoulder and elbow, allow better estimation than smaller ones, as wrist and forearm (Lowe, 2004a, 2004b).

Therefore, RULA can be effectively aided by computer processing and skeleton tracking systems. In (Haggag et al., 2013) the authors describe a framework combining the Kinect v1 with the RULA method for 3D motion analysis. The Kinect v1 skeleton tracking has also been integrated in the DHM Jack tool (Siemens, 2013), and the commercial software, Task Analysis Toolkit module (Jack-TAT), estimates, in real time, the ergonomic risk of the executed tasks. The advantages of this application of depth sensors are: the real time calculation, the portability of the device, and the reduced cost (Horejsi et al., 2013). The Kinect v1 sensor can be useful in developing ergonomic risk assessment tools, lessening the time consumption of visual-inspection assessing procedures, and removing the problem of the bias introduced by the analyst.

However, three main technical problems arose in the works using Kinect v1: the lack of wrist joints tracking, the influence of the environment lighting conditions, and the self-occlusions (in postures such as crossing arms, trunk bending, trunk lateral flexion, and trunk rotation).

The Kinect v2, presented in 2013, uses a different technology (time of-flight), and according to the specifications, it outperforms the previous version. It tracks 25 body joints including wrists (see Fig. 1); it is more robust to artificial illumination and sunlight (Zennaro et al., 2015) and more robust and accurate in tracking of human body (Wang et al., 2015). Conversely, a study (Xu and McGorry, 2015) found the non-trivial result that Kinect v1 outperforms v2 as regards average error of joint position (76 mm vs 87 mm) in seated and standing postures. Wiedemann et al. (2015) measured the accuracy of ergonomic-relevant angles computed by Kinect v2, using a marker based motion-capture system as reference. They measured high deviations of the neck angle ($-31.0^\circ \pm 9.1^\circ$) and of the upper body rotation along the longitudinal axis ($24.0^\circ \pm 3.5^\circ$), while the remaining upper body inclinations and joint angles showed higher accuracies (deviation less than 7.2° in median). Furthermore, the error in the standing postures appeared to be lower than in the sitting ones. In a very recent paper, Plantard et al. (2016) presented an interesting study on the validation of RULA grand-scores obtained using Kinect v2 data, in both laboratory and real workplace conditions. In laboratory conditions they measured angular errors between an average value of 7.7° for the simplest case (no occlusions) and 9.2° for the worst case. They also reported RULA grand-scores correctly computed for more than 70% of the conditions.

These results feature the Kinect v2 sensor to be a promising tool for postural analyses, especially for the metrics whose calculation is based on angular thresholds that tend to minimize the effect of joint angle errors, as RULA. However, some of the results reported in literature are controversial, since they are sensitive to the specific setup and to the postures adopted for the validation. We think that there is still need for further tests to strengthen the knowledge. Therefore our research questions was: is it possible to effectively use the Kinect v2 data for an early screening of exposure to WMSDs risk? The typical application scenario can be derived by the ISO standard 11228-3:2007(E), e.g. the workspace is continuously monitored by a depth camera connected to an automatic RULA evaluation system and, if critical conditions are automatically detected, additional investigations (e.g. OCRA) can be carried out.

In this paper, we present the implementation of a software tool called K2RULA, a fast, semi-automatic, and low-cost tool, based on the Kinect v2. We validated the proposed tool with two experiments. In the first one, we compared the grand-scores from K2RULA with the ones obtained with data collected by a reference optical motion capture system. In the second experiment, we compared the grand-scores obtained from K2RULA, Jack-TAT and a RULA expert.

2. Method

2.1. K2RULA software

We implemented K2RULA using C#, Windows Presentation Foundation libraries (.NET framework) and Microsoft Kinect for Windows SDK 2.0. The GUI of the K2RULA tool allows to select the video stream to be visualized (depth or infrared), and to activate a secondary window for the RBG stream (Fig. 2). The button “Real Time RULA” evaluates the RULA grand-score of the current posture. Furthermore, playback control buttons allow the execution of an offline analysis on a recorded file.

2.1.1. The RULA method

The RULA method consists in the fulfillment of an assessment grid, where the human body is divided in two sections (Section A: upper arm, lower arm, and wrist; Section B: neck, trunk, and legs). A score is calculated using three tables. The first two tables give the posture scores of the body segments. Each one of these scores is then corrected according to the frequency of the operations and the force load on the limbs. The third table takes as input the previous scores and returns a grand-score. An action level list indicates the intervention required to reduce the risks of injury of the operator:

- 1–2 grand-score: the posture is acceptable if it is not maintained or repeated for long periods,
- 3–4 grand-score: further investigation is needed and changes may be required,
- 5–6 grand-score: investigation and changes are required soon,
- 7 grand-score: investigation and changes are required immediately.

2.1.2. Data retrieval

The Kinect tracking algorithm returns a hierarchical skeleton composed by joint objects (Fig. 1). Each joint position is calculated in real time as the average of the positions stored in a 300 ms memory buffer (about 10 valid frames at 30 Hz) to minimize