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Real time RULA assessment using Kinect v2 sensor

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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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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

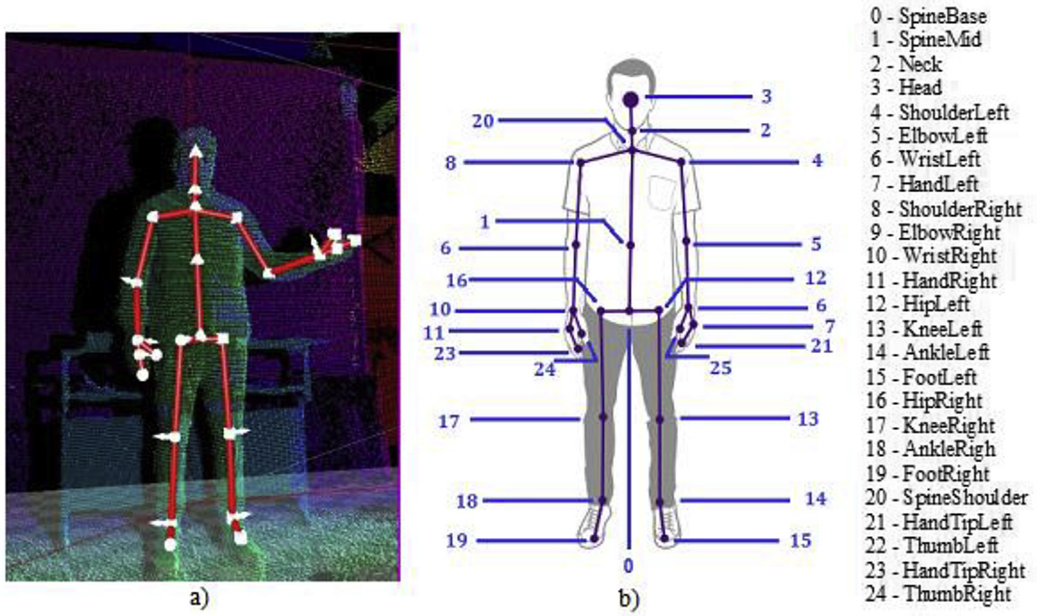

Fig. 1. The skeleton returned by Kinect for Windows SDK 2.0. a) Depth map and skeleton visualized by the Microsoft Kinect Studio v2.0; b) Joints position with respect to the body as reported by Microsoft HIG (Microsoft, 2014).

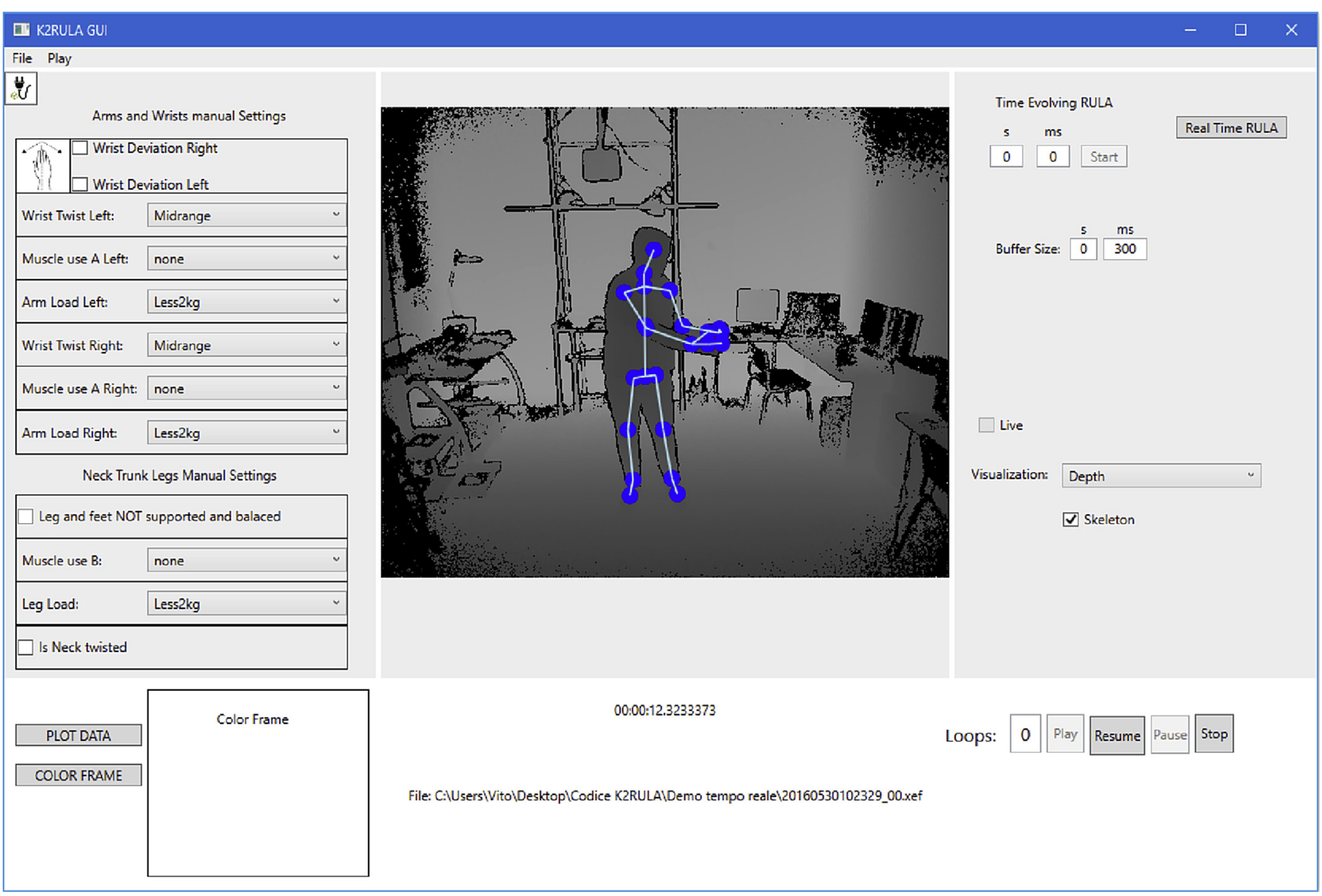

Fig. 2. GUI of the K2RULA application.

jittering. If the sensor is not able to track a joint (e.g. occlusion), its position is inferred (inferred joints) from the surrounding joints by the Microsoft SDK.

The K2RULA algorithm requires only 19 of the 25 tracked joints. RULA parameters are trivially evaluated from geometrical angles between the joints. However, for some angles, we need additional processing.

We defined the trunk vector as the vector connecting the spinebase (from Windows SDK nomenclature) to the spine-shoulder, respectively approximately corresponding to the mid posterior superior iliac spine (Wu et al., 2002) and the incisura jugularis (Wu et al., 2005).

For the *upper arms flexion/extension* we computed the angle between the trunk vector and the vector corresponding to the projection of the upper arms on the sagittal plane. The latter is evaluated as the one passing through the trunk vector and perpendicular to the straight line connecting the shoulders.

The *upper arms abduction* is evaluated with the angle between the trunk vector and the vector corresponding to the projection of the upper arms on the plane passing through the trunk and parallel to the straight line connecting the shoulders.

For the *shoulder abduction* we computed the angle between the vector connecting the spineshoulder to the neck and the vector connecting the spineshoulder to the shoulder under analysis.

To evaluate the *working position of the lower arm* with respect to the midline of the body and the side of the body, we analyzed the relative positions of the projections of the wrist, spineshoulder and shoulder on the straight line connecting the shoulders (Fig. 3).

As regards the *wrist location*, we could only approximatively assess the adduction/abduction angle. We computed the angle between the vector connecting the elbow to the wrist and the vector connecting the wrist to the handtip.

The grid assessment requires taking into account the *trunk twisting and bending* state. We verified that the sensor always returns a skeleton object with the same directions for the normal to the three joints in the trunk, regardless of the twisting state of the body (Fig. 1). Hence, we calculated the angles between the normal to the ankles (directed towards the outside of the body) and the normal to the trunk, directed towards the sensor (Fig. 4). To detect the trunk bending state we computed the angle between the straight line passing through the hip joints and the direction normal to the horizontal plane. The trunk flexion degree is trivially assessed by the angle between the direction perpendicular to the horizontal plane and the trunk vector.

We assessed the *neck flexion/extension* computing the angle between the normal to the trunk vector in the sagittal plane and the projection in this plane of the vector connecting the spineshoulder to the head. This solution leads to an overestimation of the neck back flexion with respect visual inspection. Therefore we added a positive bias of five degree in the computation of the angle on a heuristic base. We detected the *neck bending* computing the angles between the vector connecting the spineshoulder to the head and

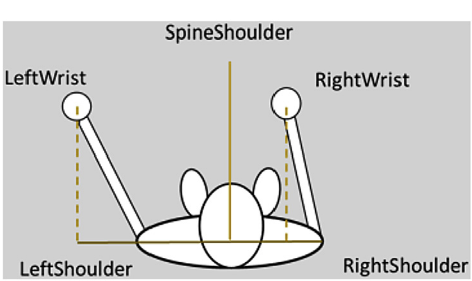

Fig. 3. Lower arms working position assessment geometrical construction.

each one of the vectors connecting the spineshoulder to the shoulders.

Despite the improvements in joint detection provided by Kinect v2, the accuracy is not sufficient to detect some important parameters for some joints, such as *wrist and neck twist*. In addition, K2RULA is not able to evaluate other factors, such as the *load on arms* and the kind of *muscle use*, that affect the RULA grand-score. As solution, we implemented default settings, and provided a simple GUI for the operator to set them (Fig. 5).

2.1.3. Functionalities

The “Real Time RULA” button activates the display of the RULA scores panel (Fig. 6).

This window provides the scores of each body section for both sides, the computed angles, and the grand-score, and saves the report on a text file. The action level is visualized with a color-coded background varying from green (grand score 1–2) to red (grand-score 7). Furthermore, the inferred joints are evidenced with red circles on the skeleton to highlight the reliability of the assessed scores.

Another functionality of K2RULA is to process continuously a recorded file in the standard Microsoft format (.xef). The software calculates the grand-score for each of the frames and generates a report, exportable in a comma separated values file, while visualizing an interactive timeline plot. By clicking on one point of the graph, a pop-up label displays the RULA grand-score for that instant (Fig. 7).

This functionality allows to continuously evaluate the working activities and to spot for critical conditions.

2.2. Experiment 1: validation with an optical motion capture system

In this experiment we studied the agreement between the K2RULA tool and a reference tracking system. We define our *hypothesis 1*: K2RULA RULA grand-scores are in accordance with an optical motion capture system.

2.2.1. Equipment

To run K2RULA, we used a Kinect v2 connected to a PC with a CPU Intel® Core™ i5-4200 2.50 GHz, 4 GB RAM, GPU NVIDIA GeForce GT 740 M, OS Windows 8. The reference tracking system was a BTS SMART-DX 5000 optical motion capture systems (BTS-Bioengineering, 2016) composed by 8 infrared digital cameras, with acquisition frequency of 100 Hz, and one PC with a CPU Intel® XEON E5640 2.67 GHz, e 3 GB RAM, OS Windows XP. We used the SMART Suite software for raw data acquisition and processing (BTS-Bioengineering, 2016).

2.2.2. Procedure

We selected 15 static postures: nine of them (Fig. 8) from the EAWS form (IAD, 2012), and six (Fig. 9) extracted from a booklet of the European campaign against musculoskeletal disorders (Colombini et al., 2012).

We recruited a volunteer (male, age 26, height 180 cm, and weight 80 kg) as an actor to simulate the aforementioned postures.

We positioned eighteen markers (1.0 cm diameter reflective spheres) on anatomical landmarks, as suggested in (Wu et al., 2005) (see Table 1 and Fig. 10). For specific landmark choices we referred to the literature: head (Xu and McGorry, 2015), shoulders and neck (Wiedemann et al., 2015), elbows (Mackey et al., 2004; Cutti et al., 2005), wrist centers (Cutti et al., 2005; Aguinaldo et al., 2007), and the pelvis girdle (Ferrari et al., 2008).

We positioned the Kinect in front of the actor at a distance of about 240 cm and at a height of 180 cm from the ground. The actor

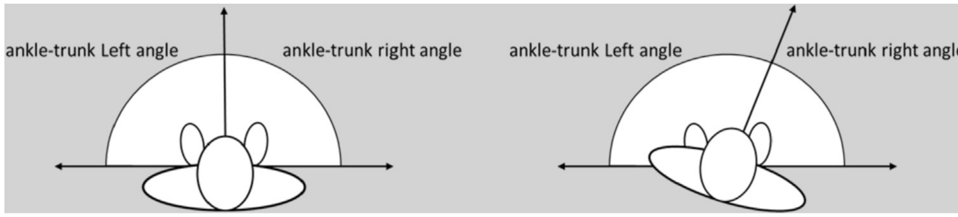

Fig. 4. Trunk twisted detection scheme.

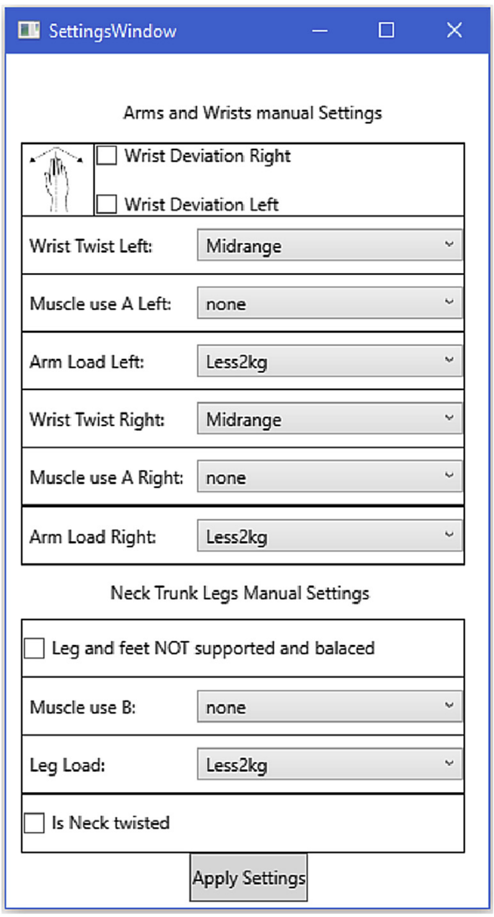

Fig. 5. Window interface for manual settings and default values.

was in the center of the area framed by the optical motion capture system in a laboratory with controlled lighting conditions (400lx). We recorded simultaneously the static postures with both the tracking systems and synchronized them according to the same event-based procedure as in (Xu et al., 2015).

2.2.3. Data analysis

We imported the coordinates from the optical motion capture system in a 3D CAD parametric model (Autodesk Inventor professional 2017), and we measured the required angles. We then computed the RULA grand-scores using the RULA Employee Assessment Worksheet (Hedge, 2000).

We assessed the agreement between the two systems by using two-dimensional contingency tables (Fleiss et al., 2004). We computed the proportion agreement index (p_0), and the strength of agreement on a sample-to-sample basis as expressed by linear weighted Cohen's kappa.

2.3. Experiment 2: validation with RULA expert and comparison with the Jack TAT

In the second experiment, we compared the K2RULA tool with a human RULA expert and with the Jack TAT. We defined our:

- *hypothesis 2*: K2RULA grand-scores are in agreement with the ones obtained by the RULA expert;
- *hypothesis 3*: the K2RULA provides better results than the Jack Task Analysis Toolkit

2.3.1. Equipment

We collected simultaneously data with a Kinect v2, a Kinect v1, and video with a Webcam Logitech® Hd Pro C920. Two identical PCs (CPU Intel® Core™ i5-4200 2.50 GHz, 4 GB RAM, GPU NVIDIA GeForce GT 740 M, OS Windows 8) ran our K2RULA and the TAT software tool version 8.0.1 (based on Kinect v1).

2.3.2. Procedure

We used the same 15 static postures of experiment 1. We recruited a RULA expert (an occupational doctor working for INAIL,[1] with more than 10 years of practice) and one volunteer (male, age 28, height 170 cm, weight 72 kg) as actor. During the experiment, we positioned the two Kinect sensors and the video camera (one above the other) in front of the “actor” as in the previous experiment in a laboratory with controlled lighting conditions (400lx). While the actor was keeping each static pose for a few seconds, we recorded each posture. We assessed the RULA grand-scores using both the K2RULA and the Jack-TAT. The RULA expert analyzed offline the recorded video of each posture and assessed the RULA grand-scores.

2.3.3. Data analysis

We carried out the comparison between the two Kinect based (KB) methods using as baseline the expert evaluation, as in (Diego-Mas and Alcaide-Marzal, 2014). We assessed the agreement between results as done in experiment 1.

3. Results

3.1. Experiment 1

Fig. 11 shows the RULA grand-scores for the body left and right side obtained with the K2RULA and the optical motion capture system.

These results indicate “perfect” agreement between the two systems (see Table 2) in the Landis and Koch scale (Landis and Koch, 1977).

[1] The INAIL, the National Institute for Insurance against Accidents at Work, in Italy is the public authority that manages the mandatory insurance against occupational accidents and diseases.

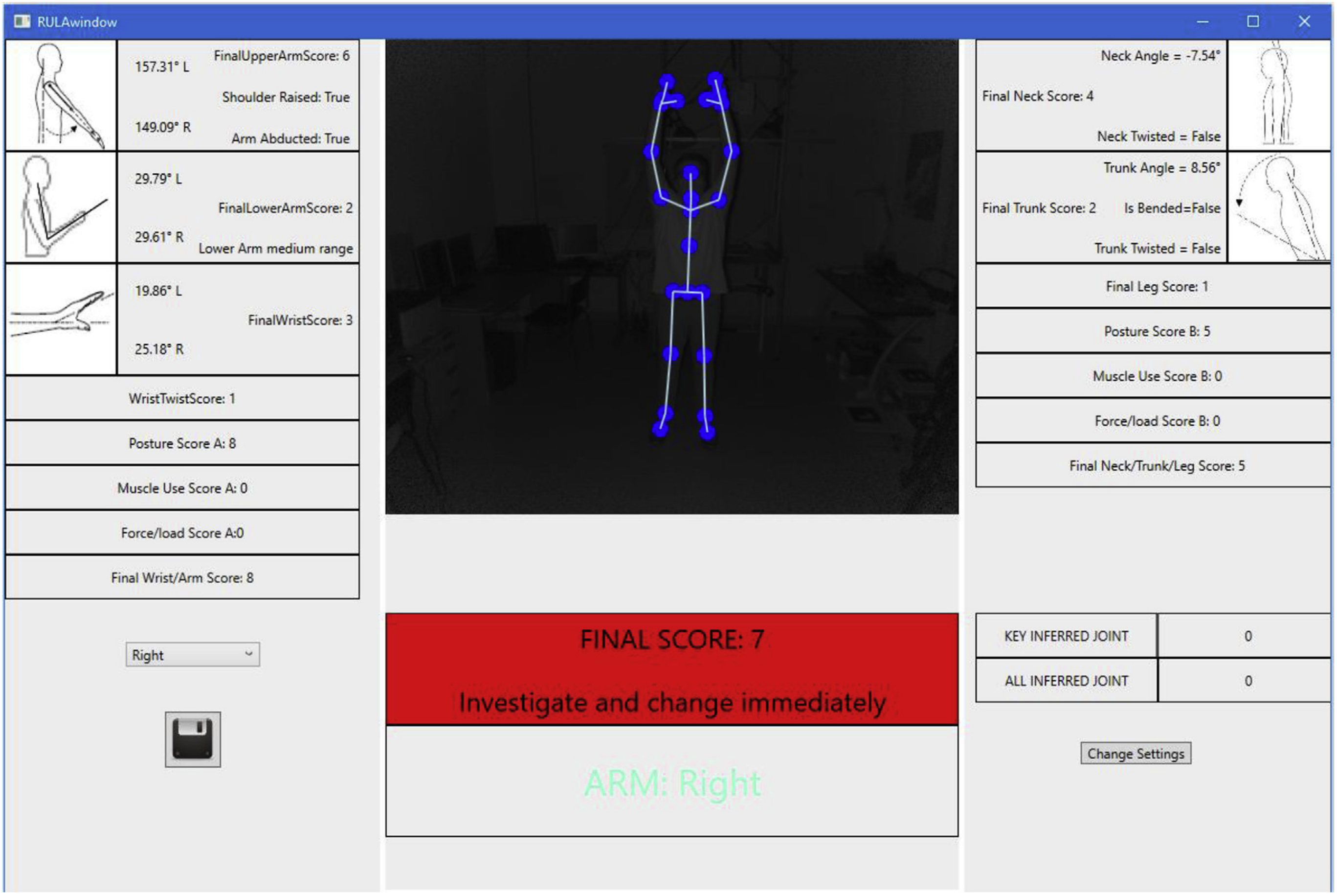

Fig. 6. The RULA scores panel.

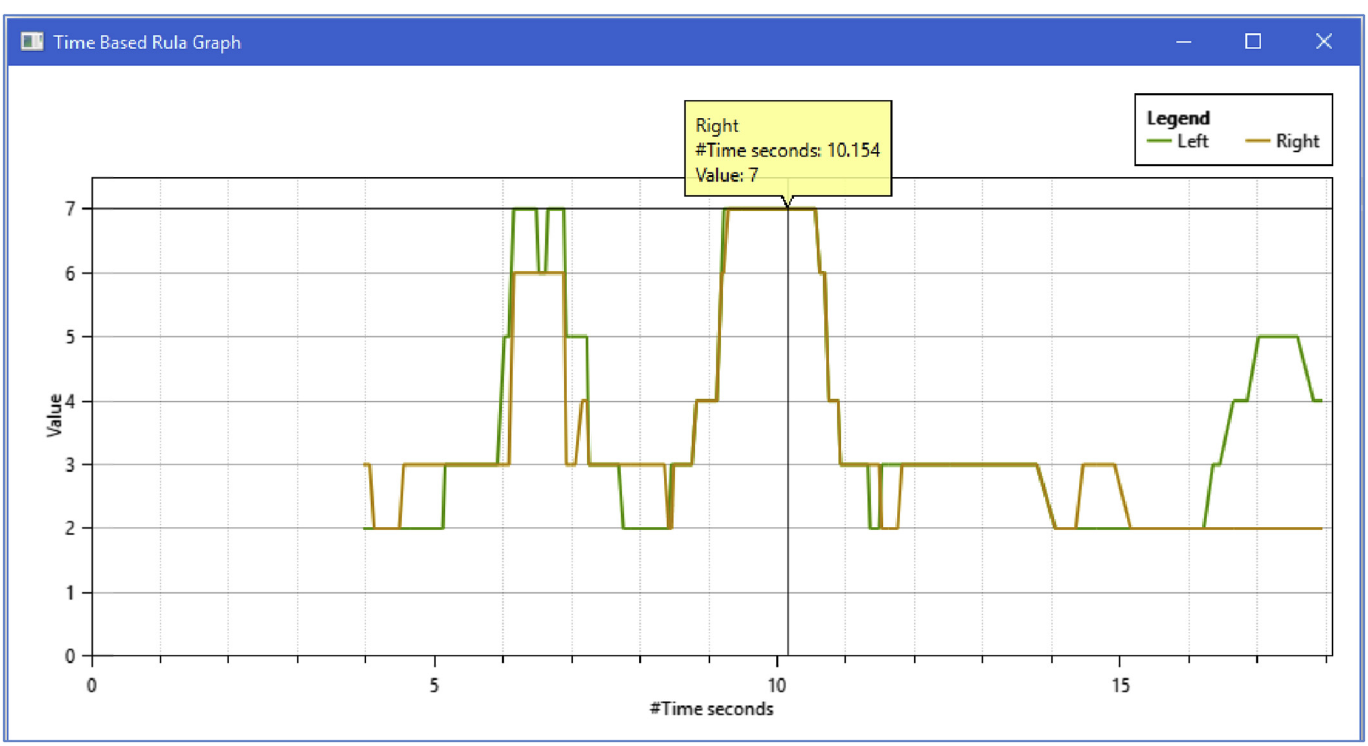

Fig. 7. Grand-scores plot for an offline analysis on a recorded file: postures at seconds 6–7 and 9–11 are critical and require further analysis.

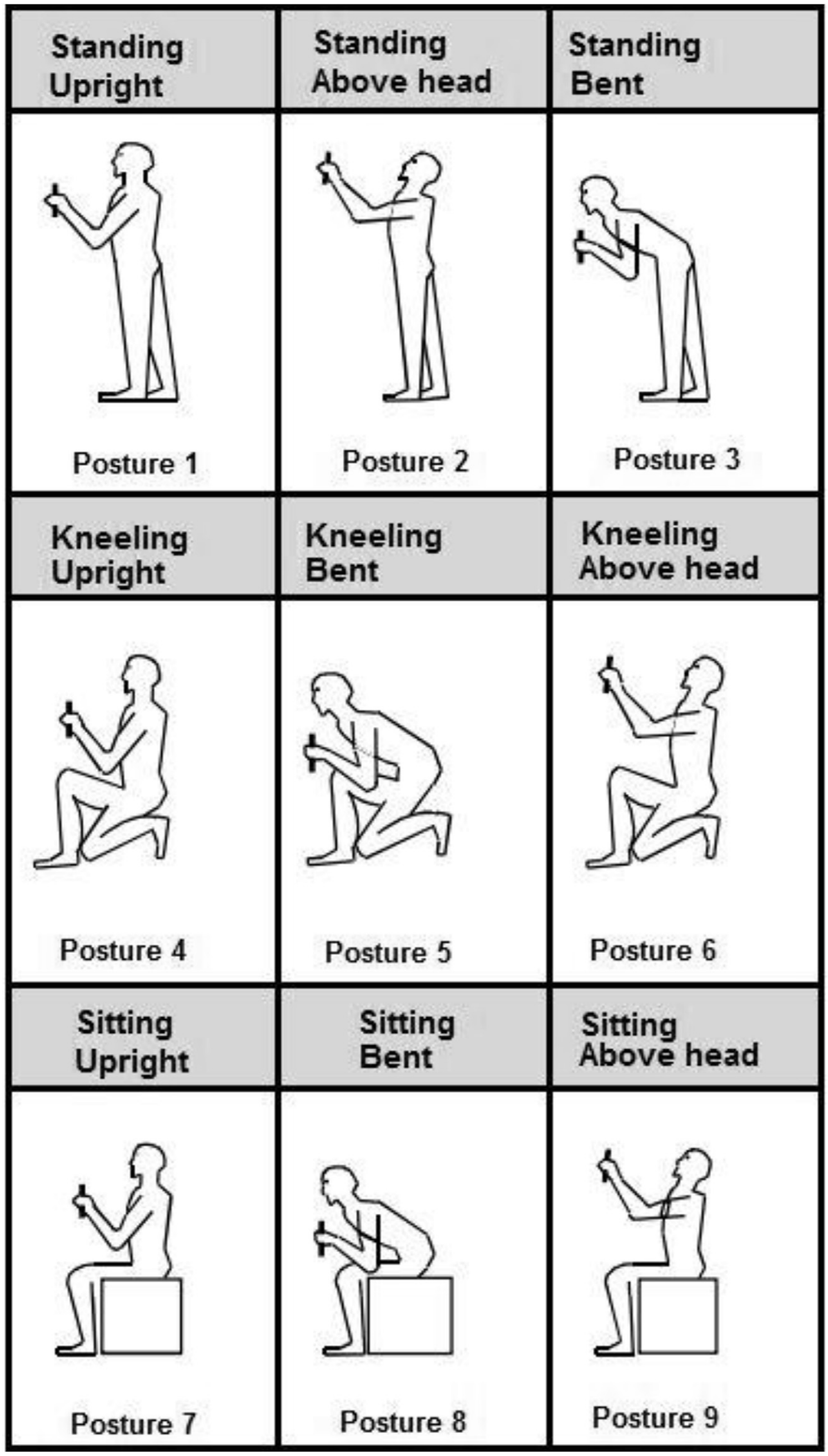

Fig. 8. Postures belonging to the EAWS form v1.3.4.

To validate the statistical significance of this result, we also tested *the null hypothesis that the observed agreement is accidental*, by referring the value of the critical ratio z to tables of the standard normal distribution. Rejecting the null hypothesis ($p < 0.001$) for both the body left and right side, allowed us to confirm the *hypothesis 1*: K2RULA grand-scores are in accordance to the RULA assessments obtained with an optical motion capture system.

3.2. Experiment 2

Fig. 12 shows the RULA grand-scores for the K2RULA and the Jack-TAT compared with the expert evaluation as baseline.

These results indicate "perfect" agreement between the expert and the K2RULA and just "fair" agreement between the expert and the Jack-TAT (see Table 3).

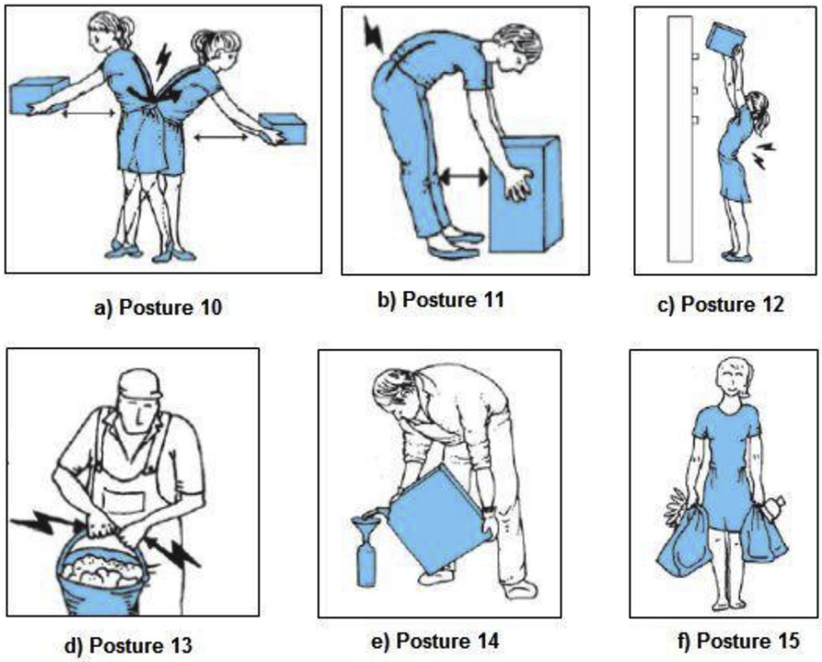

Fig. 9. From image a) to e) the five most common awkward postures, in image f) the posture used as basis for comparison. (Source: http://www.inail.it/internet_web/wcm/idc/groups/internet/documents/document/ucm_portstg_093067.pdf).

Table 1
The anatomical landmarks for reflective markers positioning, the Kinect-identified joint names and their motion tracking system-based counterparts.

Body part	Anatomical landmarks	Kinect-identified joint names	Motion tracking system-based counterparts
Head	Left/Right Temporal Regions (LTR/RTR)	Head	(LTR + RTR)/2
Torso	Left/Right Medial end of the Clavicle (LMC/RMC)	(Not present)	(LMC + RMC)/2
Neck	C7	Neck	(C7 + (LMC + RMC)/2)/2
Left shoulder	Left Acromion (LA)	Left Shoulder	LA
Right shoulder	Right Acromion (RA)	Right Shoulder	RA
Left elbow	Left Lateral Humeral Epicondyle (LLHE), Left Medial Humeral Epicondyle (LMHE)	Left Elbow	(LLHE + LMHE)/2
Right elbow	Right Lateral Humeral Epicondyle (RLHE), Right Medial Humeral Epicondyle (RMHE)	Right Elbow	(RLHE + RMHE)/2
Left wrist	Left Radial Styloid (LRS), Left Ulnar Styloid (LUS)	Left Wrist	(LRS + LUS)/2
Right wrist	Right Radial Styloid (RRS), Right Ulnar Styloid (RUS)	Right Wrist	(RRS + RUS)/2
Left hip	Left Anterior Superior Iliac Spine (LASIS)	Left Hip	LASIS
Right hip	Right Anterior Superior Iliac Spine (RASIS)	Right Hip	RASIS
Sacrum	Sacrum (S)	Spine Base	S

Table 2
Observed agreements between the K2RULA and the optical motion capture system, linear weighted Cohen's kappa and Z-test results.

Body side	P_o	Cohen's kappa	Agreement (Landis and Koch scale)	z (k/sqrt (var))	p value	Null hypothesis
Left	0.97	0.87	Perfect	4.38	<0.001	Reject
Right	0.97	0.87	Perfect	4.78	<0.001	Reject

To validate the statistical significance of these results, we also tested *the null hypothesis that the observed agreement is accidental.*

Rejecting the null hypothesis ($p < 0.001$) for the agreement between the expert and the K2RULA allowed us to confirm the *hypothesis 2*: K2RULA grand-scores are in agreement with the ones obtained manually by the RULA expert. On the contrary, accepting the null hypothesis ($p = 0.412$) for the agreement between the expert and the Jack-TAT allowed us to confirm the *hypothesis 3*: K2RULA provides better results than the Jack Task Analysis Toolkit.

4. Discussion

4.1. Main contributions

In the first experiment, the RULA grand-scores, returned by the two methods, were identical in 24 postures of the 30 considered. This result is in accordance with the outcomes presented by Plantard et al. (2016). The only six differences were due to detection of the arm abduction and the trunk flexion where K2RULA

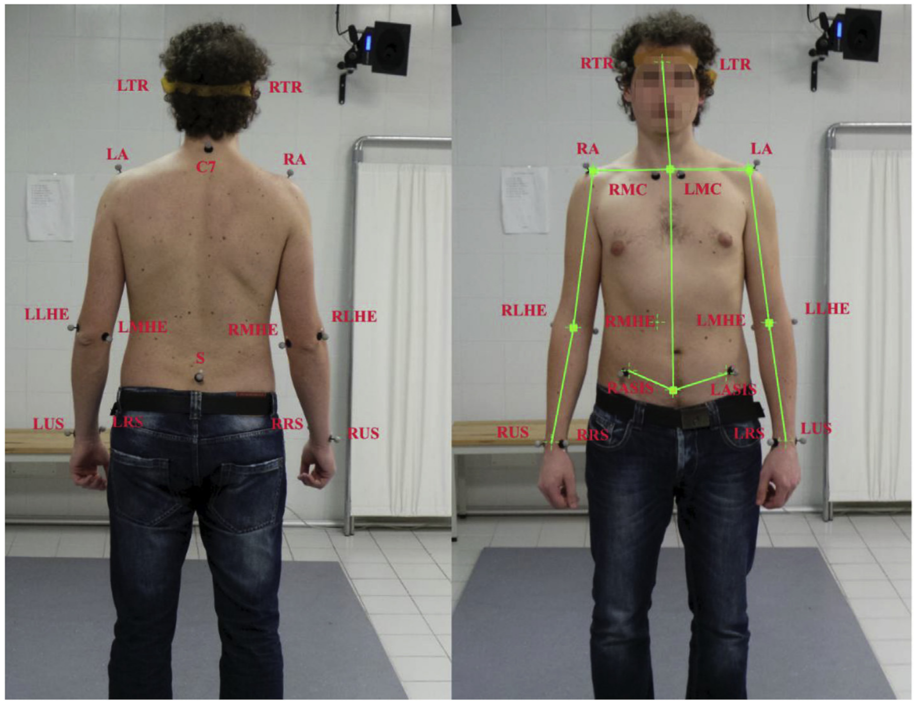

Fig. 10. The anatomical landmarks for reflective markers positioning, on the right the skeleton body model generated with the 3D CAD tool is overlaid in green.

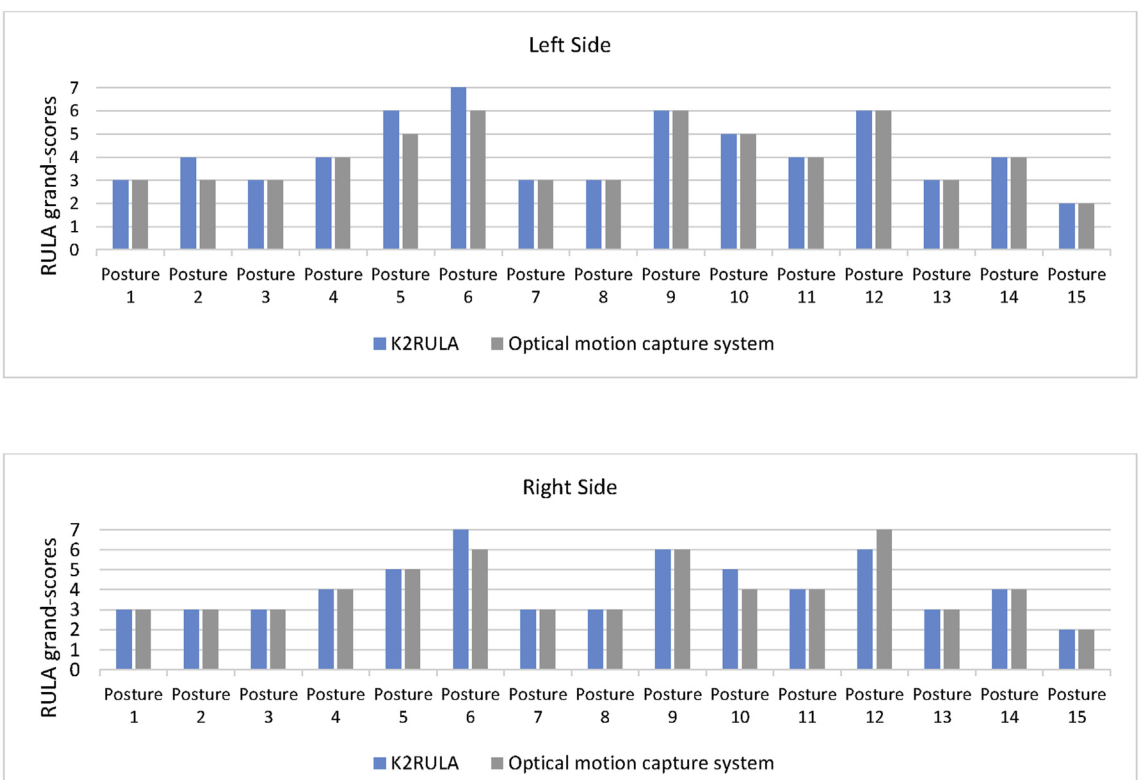

Fig. 11. RULA grand-scores for the body left and right side.

overestimated the grand-score (+1). The RULA assessment method, based on wide angle ranges, effectively compensates the joint position differences between the two tracking systems, indeed present as reported in the literature.

In the second experiment, the KB methods reported exactly the expert grand-scores for postures one, four, seven, eight, ten, and fourteen (Fig. 12). In posture two, Jack-TAT underestimated the ergonomic risk, returning a low score for the neck. Analyzing the

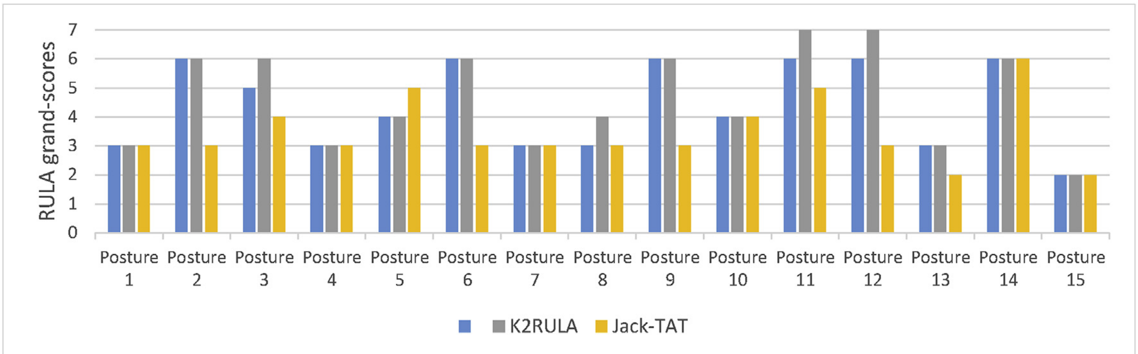

Fig. 12. KB methods vs Expert evaluation.

Table 3
Observed agreements, linear weighted Cohen's kappa and Z-test results.

Methods	Po	Cohen's kappa	Agreement (Landis and Koch scale)	z (k/sqrt (var))	p value	Null hypothesis
Expert- K2RULA	0.96	0.84	Perfect	3.87	<0.001	Reject
Expert- Jack	0.82	0.34	Fair	0.82	0.412	Accept

video frame, the neck appears back flexed. Jack-TAT was not able to detect this situation. In posture six, the operator is kneeling with outstretched hands high above the level of the shoulders. The neck and forearm have high scores, involving a high ergonomic risk. The expert and K2RULA returned the same severe grand-score. Jack-TAT gave a lower grand-score. Jack-TAT showed some problems with kneeling postures and sometimes it was not able to track the skeleton. In posture nine, the operator sits with both arms raised over shoulder height. The expert and K2RULA returned the same grand-score whereas Jack-TAT gave a lower one. Posture ten is characterized by the trunk rotation and by the left arm crossing the sagittal plane. K2RULA and the expert gave the same score for each body section. Jack-TAT in this case returned the same grand-score, but this correspondence is just accidental as Jack-TAT underestimates the arm section and overestimates the neck section. In posture eleven, the trunk is highly flexed forward. Our tool returned the highest grand-score since it detected even a small twisting and a bending of the trunk. In posture twelve, Jack-TAT did not detect the neck back flexion and underestimated the arm section.

Jack-TAT seems to underestimate the ergonomic risk returning frequently a grand-score lower than the one estimated by the expert (mean error $\varepsilon = -0.933$, error std. dev. $\sigma = 1.34$). K2RULA slightly overestimates the risk (mean error $\varepsilon = 0.267$, error std. dev. $\sigma = 0.44$). However, this overestimation is conservative and hence consistent with the goal of this tool. K2RULA showed a “perfect” agreement with respect to the expert ($P_0 = 0.96$, $k = 0.84$). Our results showed a slightly better agreement than that obtained by Plantard et al. (2016), although their data were acquired in real work conditions.

4.2. Limitations of the study and possible research developments

We tested our tool in a laboratory set-up with controlled lighting conditions and without occluding objects. This is the best working condition for the Skeleton Tracking algorithm for Kinect v2 (Wang et al., 2015) and Kinect v1 (Microsoft, 2013), and our results suffer only from the actor's body self-occlusions. We need to further investigate the behavior of our tool in a real working environment. Moreover the hands configuration plays a key role, thus our future research will address the hand tracking limits of the Kinect v2. We are planning to apply data fusion techniques to data gathered from the depth sensor and from low cost non-intrusive wearable devices. The availability of such data would probably allow the implementation of methods and tools able to assess fatigue indexes more detailed than the RULA score, such as OCRA index, moving from static postures analysis to continuous measurement.

5. Conclusions

In this paper, we presented K2RULA, a real time semi-automatic RULA evaluation system based on Kinect v2. It allows to speed-up the detection of critical conditions and to reduce the subjective bias. K2RULA is able to analyze off-line data and to save the results for deeper ergonomic studies. We validated the proposed tool with two experiments, using as baseline an optical motion capture system and a RULA expert, proving the reliability of K2RULA as a faster alternative to classical visual inspection evaluation. We also compared it with a commercial software, the Jack-TAT, based on the Kinect v1 sensor. In summary, we demonstrated in laboratory condition that:

1. K2RULA grand-scores are equivalent to the assessments obtained with an optical motion capture system;
2. K2RULA grand-scores are in perfect agreement with a RULA expert evaluation;
3. K2RULA outperforms the Jack-TAT tool, based on Kinect v1.

We can conclude that the proposed system can be effectively used as a fast, semi-automatic and low-cost tool for RULA analysis.

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