Real time RULA assessment using Kinect v2 sensor

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Abstract

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. Recently, researches demonstrated accuracy improvements of the new Microsoft Kinect[1] v2 sensor. In this paper, we exploit it for RULA assessment of posture awkwardness as a fast alternative to the classical visual inspection methods. We present K2RULA, a semi-automatic software, aimed at detecting awkward postures in real time. We evaluated the agreement of the scores returned by the proposed application with those obtained by a RULA expert rater finding a statistical perfect match according to the Landis and Koch scale (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).

Keywords: Kinect v2, RULA, Ergonomics

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 is still fairly common. Taking also into account the high effect on welfare costs, it is mandatory to apply policies aimed at minimize 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. According to the accuracy of the data collection and the measurement techniques that are used (Li and Buckle, 1999), we can classify these procedures into three groups: i) self-report; ii) direct measurement, and iii) observational methods. 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 consist of direct observation of the worker during his work shift. Due to their ease of use, they are widely applied in industry. 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. These are relatively low cost methods and do not interfere with the working process. The have the main disadvantage to require a field expert who performs a time consuming analysis of the postures, of the repetition rate, and of the involved forces. The biggest drawbacks of the observational methods are the collection inaccuracy and the low sampling rate. The use of video-based systems and computer vision techniques improved the sampling rate (Pinzke and Kopp, 2001; Fıglalı et al., 2015), and allowed researchers to study the validity and the interrater reliability of those methods. It has been reported that better estimation validity is achieved from observing larger body parts, as shoulder and elbow, (Lowe, 2004a)) than smaller

[1] Kinect™ is a Microsoft Corporation registered trademark

body parts, as wrist and forearm (Lowe, 2004b)). A large field study showed that observational methods have better interrater reliability if a wider fixed-width categorization strategy (30° vs 10°) is used when classifying the angles between body segments. In this study, As regards the different body parts, the posture parameters of elbows flexion, forearms supination and pronation, neck twisting, upper arms flexion and extension, and upper arms inward and outward rotation, had average interclass correlation coefficients (ICCs) greater than 0.50. The worst ICCs were found among left and right wrist ulnar and radial deviation, neck lateral flexion, and trunk twisting postures (ICCs ≤ 0.20) (Bao et al., 2009). The inter rater reliability of the RULA method, that uses wide fixed-width categorization strategy, was assessed among four trained raters in a study on office workers. ICCs for RULA sub-scores ranged from 0.85 to 0.99 and ICC for the grand scores was 0.86, furthermore authors observed that the agreement tended to grow with the experience acquired by the raters (Robertson et al., 2009).

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 very 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 show that Kinect v1 is accurate enough to capture human bodies in a workplace environment. The accuracy and robustness of the provided joint positions (skeleton tracking) are promising for clinical uses (Fern'ndez-Baena et al., 2012; Kurillo et al., 2012), and for applications that require to fill in an ergonomic assessment grid (Diego-Mas and Alcaide-Marzal, 2014; Plantard et al., 2015). Patrizi et al. compared a marker-based acquisition system with a Kinect v1 for the assessment of the human posture during working tasks and the recommended weight limit in the NIOSH lifting equation. Their results suggest that the depht sensor may be successfully used for assessing the risk of the working activities (Patrizi et al., 2015). Two works exploited Kinect v1 to compute an ergonomic score based on the EAWS method (Nguyen et al., 2014; Kruger and Nguyen, 2015). The authors applied digital image processing algorithms to depth images, computed body parameters to detect worker posture, and tested the tool in an industrial environment to improve the comfort of the workplace. However, their system shows some limits, particularly with respect to the accuracy in hand position detection.

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 and fill the required parameters, which are not retrieved by depth cameras (e.g. force/loads, occurrence of static/repetitive muscular activity and so on). This prevents a widespread use of these methods for the evaluation of the exposure to ergonomic risk factors in the workplace.

A promising solution is offered by the ISO standard 11228-3:2007(E) (ISO, 2007) which 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 observational methods, the RULA (McAtamney and Nigel Corlett, 1993) represents one of the most popular, and in the aforementioned standard, it is listed among those simplified methods applicable for rapid analysis of mainly static tasks. Its application in industrial environment it has been largely studied, both using worksheet as in (Ansari and Sheikh, 2014; Rahman, 2014) or exploiting Digital Human Models (DHM) as in (Mohamad et al., 2013). Although not as detailed as the OWAS, NIOSH, OCRA, and EAWS, the RULA method requires mostly angular data, which can be easily gathered from depth cameras.

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 feature has also been integrated in the DHM Jack tool (Siemens, 2013). The system transfers the joint data, collected via the Kinect sensor, to a virtual human in the digital environment. Lastly, the Task Analysis Toolkit module (TAT), estimates, in real time, the ergonomic risk of the tasks executed by the user in the real environment. In (Horejsi et al., 2013), authors evidenced the real time calculation, the portability of the device, and the reduced cost as the advantages of depth sensors in this application. A similar work (Teeravarunyou, 2014) investigates the reliability and the advantages of a range camera for posture analysis based on the RULA applied to computer workstation usage.

Three main technical problems arose in the works using Kinect v1: the self-occlusions (in postures such as crossing arms, trunk bending, trunk lateral flexion, and trunk rotation), the lack of wrist joints tracking, and the influence of the lighting on the environment. At the same time, these works evidenced how the Kinect v1 sensor could 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.

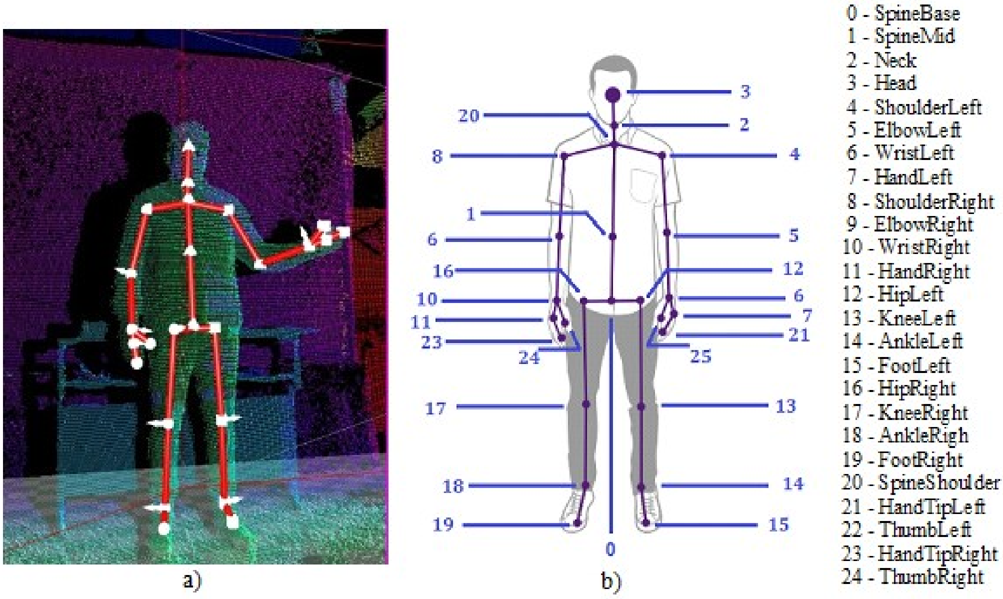

Figure 1: The skeleton returned by Kinect for Windows SDK 2.0. a) Depth map and skeleton visualized by the Microsoft Kinect Studio v2.0 : the white cubes indicate the 25 joints; the white arrows indicate normals. b) Joints position with respect to the body as reported by Microsoft HIG (Microsoft, 2014).

The Kinect v2, exploiting a time of-flight-technology, outperforms Kinect v1. It returns 5 more body joints (total of 25, see Figure 1). Several authors studied the accuracy of kinematic data provided by the Kinect v2. It is more accurate in depth measurement and it is more robust to artificial illumination and sunlight (Zennaro et al., 2015). A recent study compared the accuracy of joint position in eight seated and eight standing postures recorded by both the Kinect v1 and v2 sensors and found an average misalignment of 76 mm and 87 mm of the joint centers, respectively (Xu and McGorry, 2015). However, in this study, the comparison was done indirectly with two different sets of subjects. In a further study, the accuracy of joints tracking, during dynamic exercises, was compared using the same set of subjects by simultaneously recording data with both sensors and a motion capture system. Authors reported a better overall accuracy of joint positions in Kinect v2 than in Kinect v1, except the location of feet. The difference and variance of the actual limb lengths were smaller in Kinect 2 than in Kinect 1. The average offsets were typically between 50 mm and 100 mm. Furthermore, Kinect v2 was more reliable in partial body occlusions and the skeleton tracking latency was smaller (Wang et al., 2015).

The accuracy of skeleton joint angles obtained by the Kinect v2, was studied with respect to ergonomic relevant angles, such as upper body inclinations and rotation, neck inclination, hip (angle between trunk and upper-leg) and knee (angle between upper- and lower-leg) angles (Wiedemann et al., 2015). Authors analyzed 14 seated and 2 standing body positions, by calculating the median difference, the 97.5% percentile, and the 2.5% percentile of the Bland Altmann plots of each angle with respect to the joint angles obtained with a marker based opto-tracking system (Table I).

Table I: The median difference, 97.5% percentile (upper bound) and 2.5% percentile (lower bound) of the Bland Altmann plots of each angle.

Joint angle	**Median Difference**	**Upper bound**	**Lower bound**
Neck	8.46°	30.22°	-11.06°
Upper body inclination forwards	-4.44°	3.67°	-11.78°
Upper body lateral bending	-1.96°	3.48°	-8.10°

Upper body rotation	0.55°	28.79°	-34.47°
Hip left	7.20°	21.06°	-3.04°
Hip right	6.18°	21.59°	-5.71°
Knee left	0.26°	16.47°	-11.84°
Knee right	-0.69°	13.74°	-12.07°

The absolute median differences over all subjects and postures resolved in less than 10° per joint angle. The neck angle and the upper body rotation along the longitudinal axes showed the highest deviation in the end-range region. The remaining upper body inclinations and joint angles had accuracies with a median difference of less than 7.2°. Furthermore, in the standing postures, the differences range appeared to be significant lower compared to the sitting postures. This and the aforementioned results feature the Kinect 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.

At present time, as far as the authors know, there is no application of Kinect v2 for the assessment of the ergonomic risks in working activities.

Our main research motivation is to push a widespread use of a low-cost, automatic tool for an early screening of exposure to WMSDs risk as a fast alternative to the classical visual inspection methods. Our requirements are: (i) as automatic as possible; (ii) robust, reliable and; (iii) real time and off-line analysis. These requirements led us to the use of the RULA method supported by data collected by the Kinect v2. In this paper, we present the implementation of a novel software tool called K2RULA. The typical application scenario may be the one proposed by the ISO standard 11228-3:2007(E) where the workspace is continuously monitored by the K2RULA and, if critical conditions are automatically detected, additional investigations (e.g. OCRA) can be carried out. We assess the reliability of the proposed tool with a RULA expert evaluation. We also compare the K2RULA with a commercial solution based on the Kinect v1.

In the following sections, we present our tool, the procedures to retrieve and process the input data, and the experimental method to assess the reliability of the proposed tool.

2. Materials and methods

K2RULA was developed 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 (Figure 2). A button starts the real time evaluation of the RULA score of the current posture. Furthermore, playback control buttons allow the execution of an offline analysis on a recorded file.

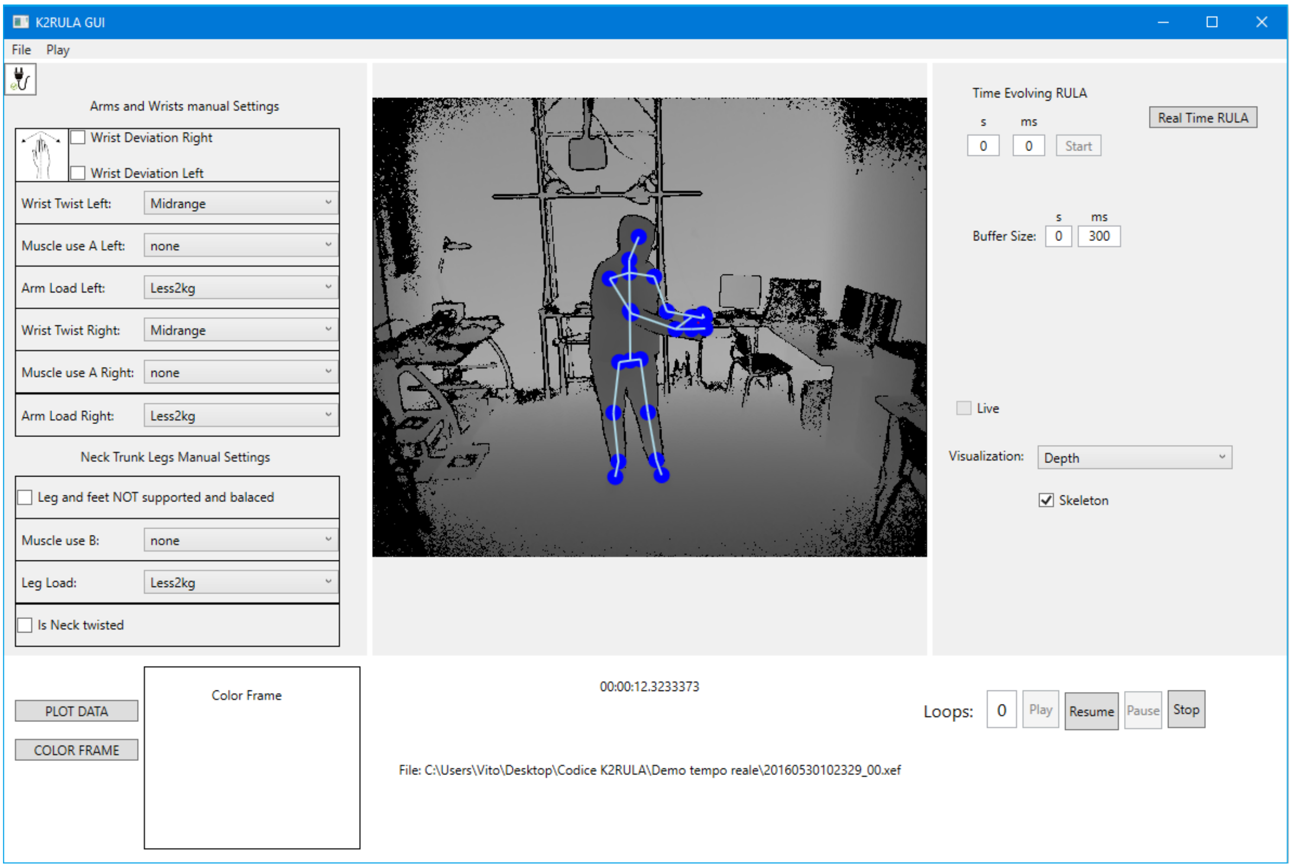

Figure 2: GUI of the K2RULA application

2.1. The RULA method

RULA, acronym of Rapid Upper Limb Assessment, 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 obtained scores and returns a grand score. An action level list indicates the level of intervention required to reduce the risks of injury of the operator:

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

2.2. Data retrieval

The Kinect skeleton tracking algorithm returns a skeleton object composed by joint objects. Joints follow a hierarchy structure starting from a root node corresponding to the spine base (Figure 1). If the algorithm is not able to reliably track a joint, its position is inferred from surrounding joint data. Each joint object contains the coordinates, the orientation and the tracking accuracy (tracked, inferred, or not tracked). The skeletal tracking joint information are buffered across different frames to minimize jittering and stabilize the joint positions over time. The position of each joint is calculated in real time as the mean of the position stored in the buffer. Our experimental results show that a buffer size of 300 milliseconds is appropriate.

K2RULA takes as input 19 of the 25 joints, and does not use the thumb, the knee, and the foot joints. Hereafter when reporting joint names we will refer to those returned by the Microsoft Kinect v2 skeleton tracking algorithm.

In most of the cases, RULA assessment parameters are trivially evaluated as angles using adjacent body segments defined by two joints. Nevertheless, to assess the RULA score we need further processing for the following parameters.

We defined the trunk vector as the vector connecting the spinebase and the spineshoulder, 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 flextion/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 and the neck and the vector connecting the spineshoulder and 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 (Figure 3).

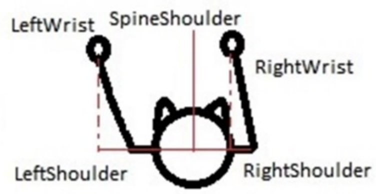

Figure 3: Lower arms working position assessment geometrical construction.

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

The grid assessment requires taking into account the *trunk twisting and bending* state. In the developing phase, 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 (Figure 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 if it is in front of the user (Figure 4). To detect the trunk bending state we computed the angle between the straight line passing through the hip joints and the direction perpendicular to the horizontal plane. The trunk flexion degree is trivially assessed with the angle between the direction perpendicular to the horizontal plane and the trunk vector.

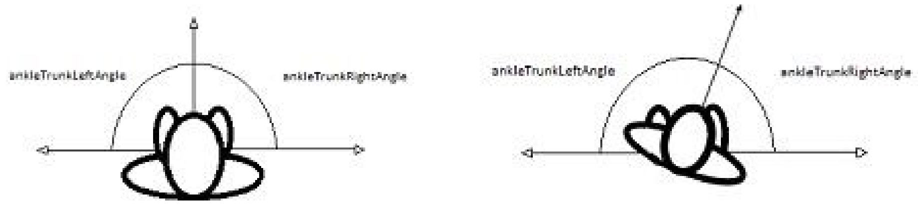

Figure 4: Trunk twisted detection scheme

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 with the head. This solution leads to an overestimation of the neck back flexion with respect visual inspection, thus we added a positive bias of five degree in the computation of the angle. We detected the *neck bending* computing the angles between the vector connecting the spineshoulder and the head and each one of the vectors connecting the spineshoulder with the shoulders.

Despite the improvements in joint detection provided by Kinect v2, the accuracy for some joints is not sufficient to detect some important parameters, 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 score. As solution, we implemented the software assuming default settings for these factors, and provided a GUI for the operator to modify manually these values, if needed, before or after running the automatic analysis (Figure 5).

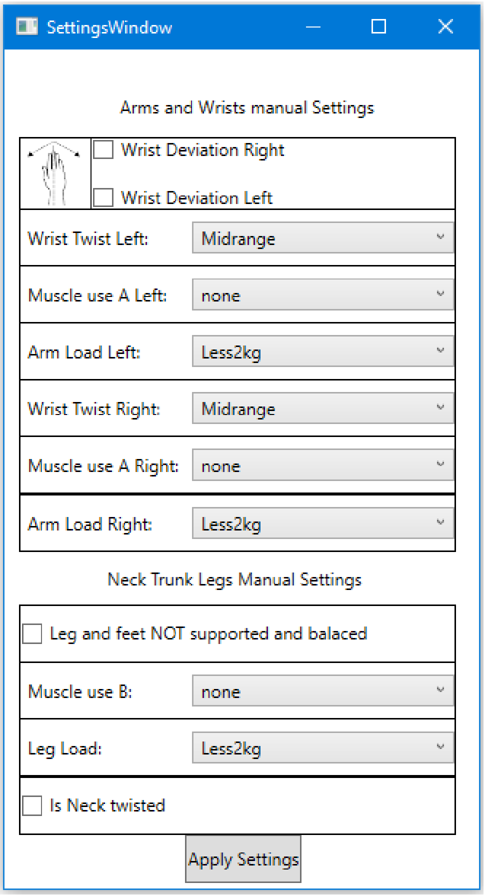

Figure 5: Window interface for manual settings and default values.

The real-time analysis returns a report with the RULA scores for both body sides (Figure 6).

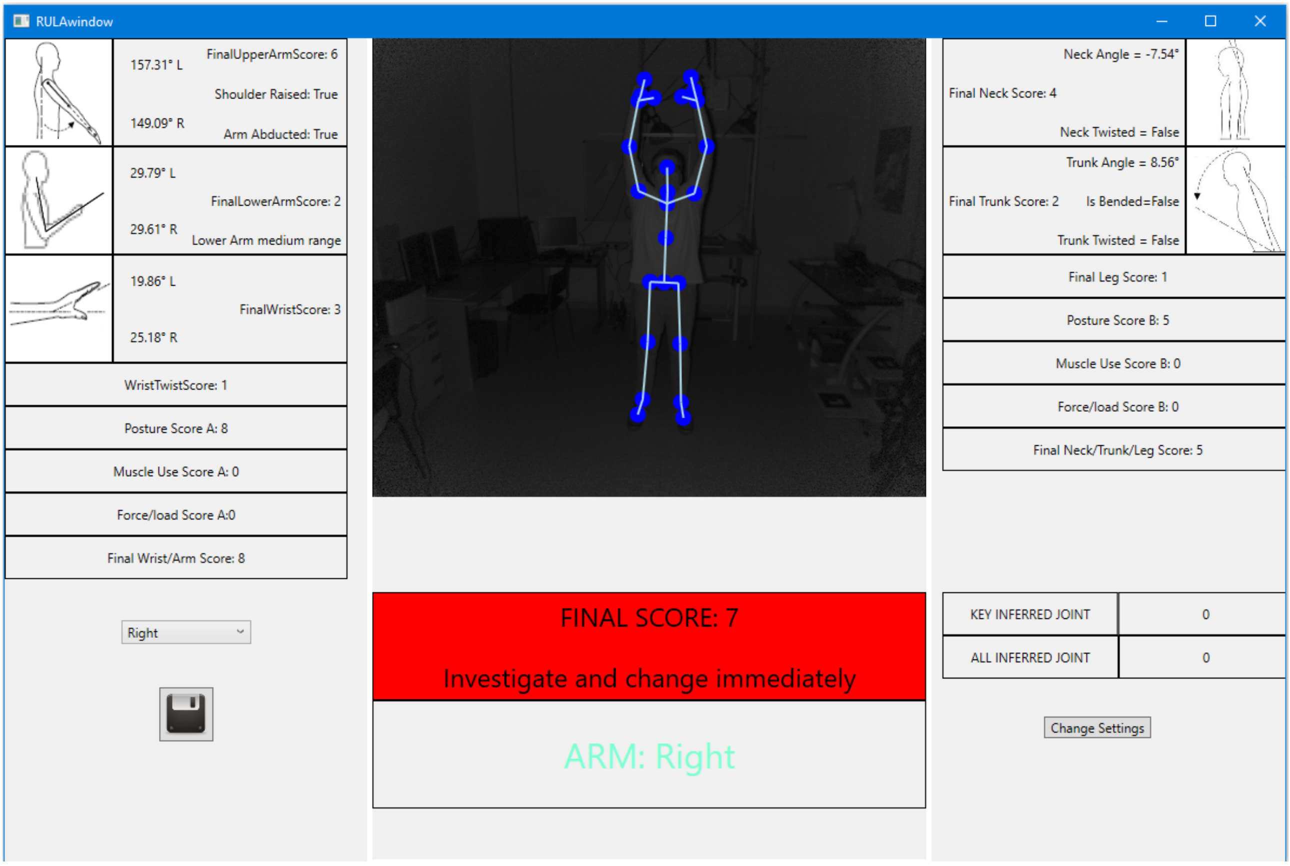

Figure 6: The report provided by the tool

It provides the intermediate scores related to the body section, the computed angles, and the grand score, saving the report on a file. The action level is associated with a color-coded background varying from green (grand score 1-2) to red (grand score 7). Furthermore, the inferred joints (i.e. not tracked) are evidenced with red circles on the skeleton to visualize the reliability of the measure.

A further functionality of K2RULA is the offline analysis on a recorded file. The tool generates a report, exportable in a comma separated values file, and visualizes an interactive plot with the grand scores. By clicking on one point on the graph, a pop-up label automatically displays the RULA score for that instant (Figure 7).

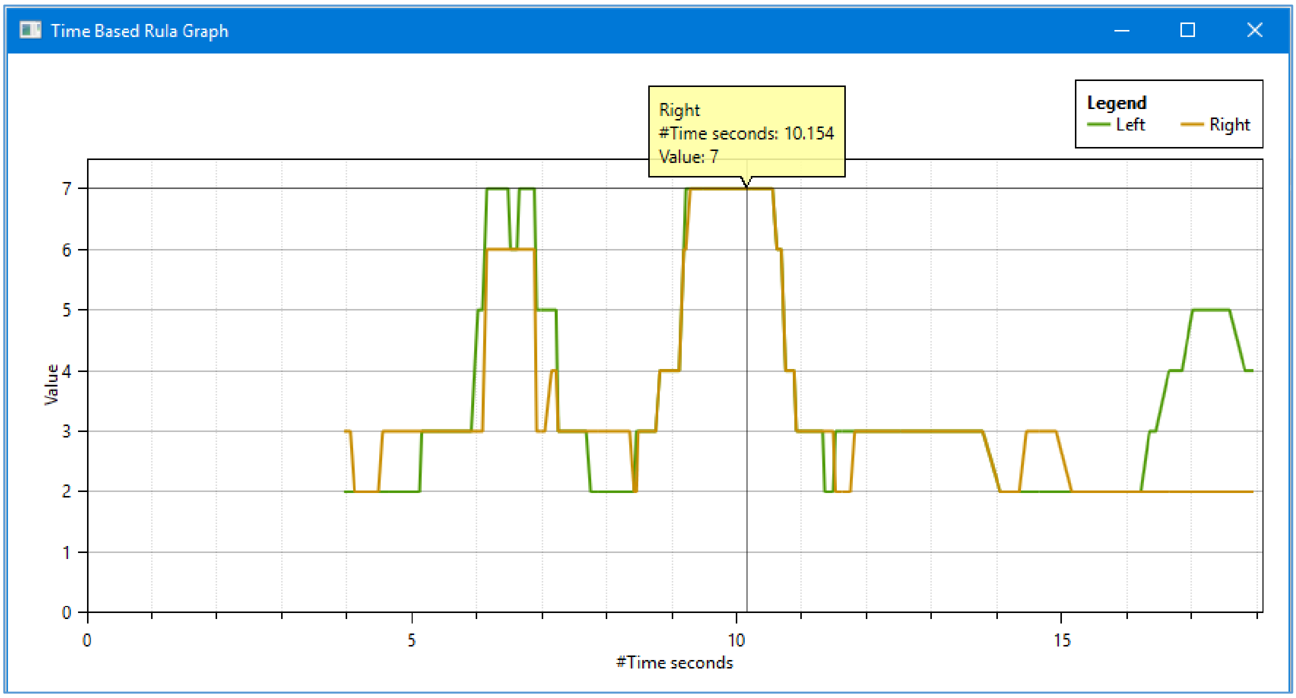

Figure 7: Grand scores plot for an offline analysis on a recorded file: postures at seconds 6-7 and 9-11 are critical and require further analysis

This functionality allows fast detection of critical conditions that can undertake further investigations.

2.3. Experimental procedure

The aim of the experimental phase was to confirm if K2RULA represents a reliable alternative to the expert visual-inspection procedure for an early stage analysis of WMSDs risk exposure. We ran two experiments, the first on static postures and the second on dynamic execution of continuous movements. We used a Kinect v2 and a Kinect v1 sensors, a Webcam Logitech® Hd Pro C920, and a 2 PCs, each one of them with a CPU Intel® Core™ i5-4200 2.50 GHz, 4GB RAM, GPU NVIDIA GeForce GT 740M, OS Windows 8.

In experiment 1, we compared our tool with both the standard visual-inspection assessing procedure, and with the Jack Task Analysis Toolkit (TAT software tool version 8.0.1 based on Kinect v1), a commercially available add-on module to Jack, Siemens PLM Software. We selected 15 static postures, significant in terms of ergonomics. Nine of them (Figure 8) belonged to the EAWS form (available at: http://ergo-mtm.it/wp-content/uploads/2013/09/EAWS-form-v1.3.4-EN.pdf), and six (Figure 9) extracted from a booklet (Colombini et al., 2012), created as part of the European campaign against musculoskeletal disorders in 2007, and updated in 2011. We selected the five most common awkward postures among those covered in the booklet.

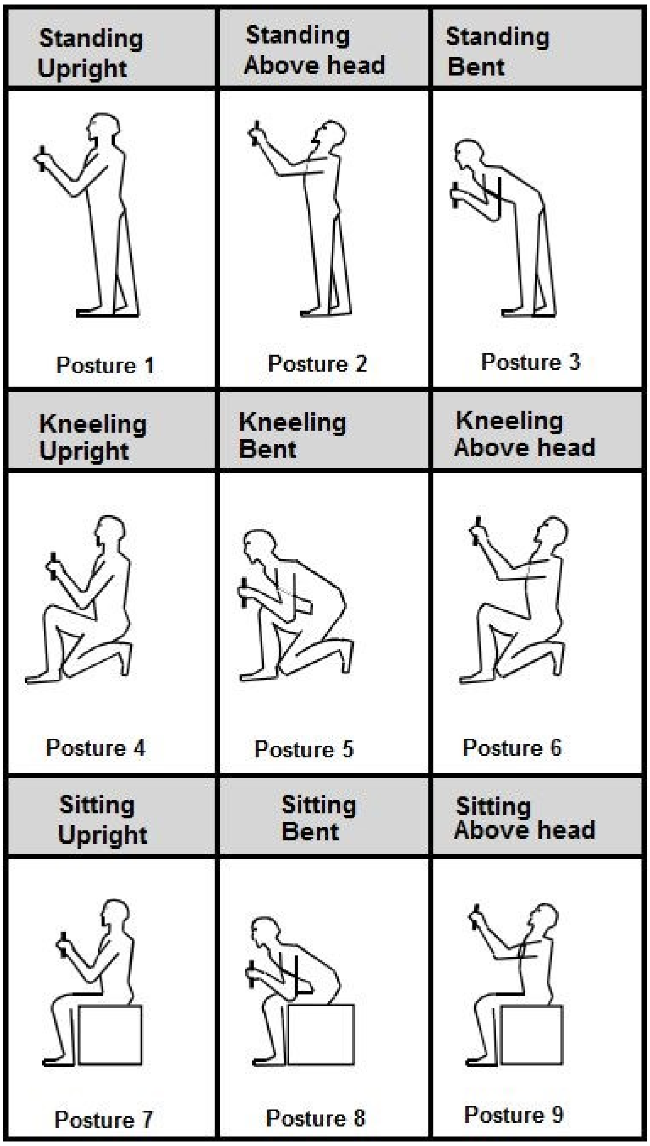

Figure 8: Postures belonging to the EAWS form v1.3.4

We recruited a RULA expert (an occupational doctor working for INAIL[2]) and one volunteer (male, age 28, eight 170 cm, weight 72 kg) as actor to simulate postures. During the experiment, we positioned the two Kinect sensors in front of the “actor” at a distance of about 240 centimeters and at an eight of 180 centimeters from the ground. While the actor was keeping each static pose for a few seconds, we recorded each posture with the Kinect v2 sensor for K2RULA, and with the webcam for the evaluator. At the same time, we assessed the RULA score with the Jack-TAT for Kinect v1. Indeed the Jack-TAT plugin for the Kinect v1 did not allow the offline analysis.

[2] The INAIL, the National Institute for Insurance against Accidents at Work, is a Public authority that manages the mandatory insurance against occupational accidents and diseases. its mission consists of: reduce workplace accidents, ensure workers involved in risky activities, ensure the reintegration into working life of injured workers, and carry out research and develop methodologies for monitoring and verification in the field of prevention and safety.

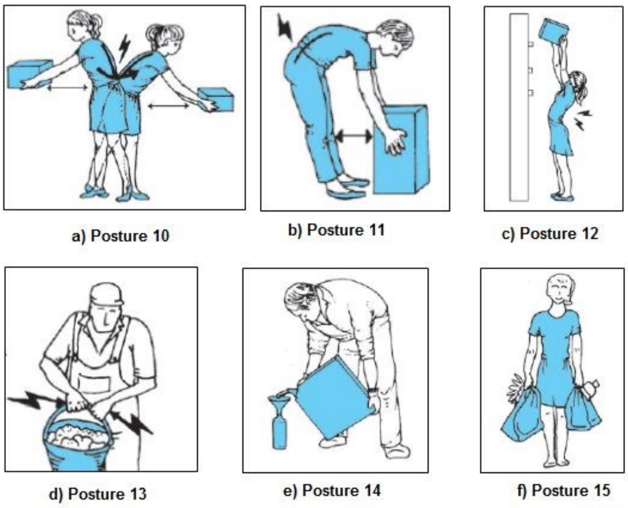

Figure 9: From image a) to e) the five most common awkward postures, in image f) the posture used as basis for comparison. (Source: http://www.inail.it/internet_web/wcm/idc/groups/internet/documents/document/ucm_portstg_093067.pdf)

The RULA expert analyzed the recorded video of each posture and assessed the RULA scores. Lastly, we computed the scores using our tool.

In experiment 2, we tested our tool on dynamic execution of continuous movements, comparing our tool with the standard visual-inspection assessing procedure. An actor executed a sequence of continuous movements that were recorded both by the Kinect v2 and by the webcam. We measured the RULA score with our tool, sampling the sequence with a period of 1 second. The expert rater used the webcam record to compute the scores in the same instants. The synchronization between the webcam video and the Kinect v2 recording was assured via the RGB stream acquired with the Kinect v2. The sequence of continuous movements under analysis lasted 14 seconds. We did not make a comparison with the Jack-TAT tool because it does not allow the offline playback of a recorded file nor saving multiple results for real-time analyses.

3. Results

We used as baseline the expert evaluation, as in (Diego-Mas and Alcaide-Marzal, 2014). For the experiment 1, we carried out the comparison between the two Kinect based (KB) methods and the scores assessed by the expert (Figure 10). We analyzed the errors of each KB method with respect to the expert rater scores. Subsequently, we analyzed the collected data to evaluate the agreement between each automatic Kinect based method and the expert evaluation.

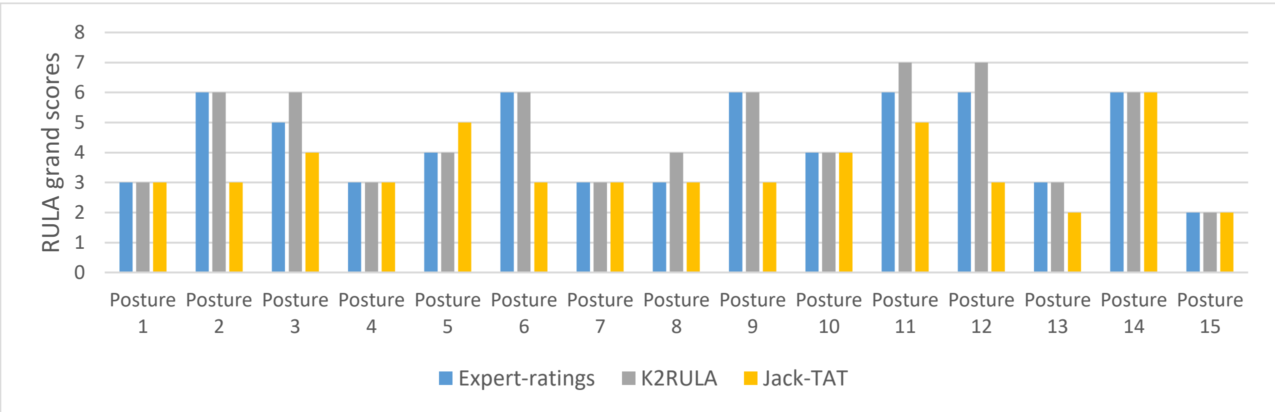

Figure 10: KB methods vs Expert evaluation

We analyzed the differences of the scores obtained with the two KB methods with respect to the expert ratings. The Shapiro-Wilk test and the Levene's non-parametric test rejected the hypothesis of normality and homoscedasticity respectively. Therefore, we applied the Friedman test to verify if the two KB methods present statistically the same difference with reference to expert ratings. This hypothesis was rejected ($\chi^2(1, 14) = 5.44$, p=.0196). Therefore, we analyzed which of the two KB methods presented the better agreement with respect to the expert's scores. We used two-dimensional contingency tables as described in (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. Next, we tested *the null hypothesis H_0 that the observed agreement is accidental*, by referring the value of the critical ratio z to tables of the standard normal distribution (Table II).

Table II: Observed agreements, linear weighted Cohen's kappa and Z-test results

Methods	**P_o**	**Cohen's kappa**	**Agreement scale (Landis and Koch)**	**z (k/sqrt(var))**	**p value**	**Null hypothesis**
Expert- K2RULA	0.96	0.84	Perfect	3.87	0.0001	Reject
Expert- Jack	0.82	0.34	Fair	0.82	0.4120	Accept

In the experiment 2, we compared the scores returned by our tool with those assessed by the expert rater. We selected 14 frames (one per second) for the analysis. Figure 11 shows the relative scores.

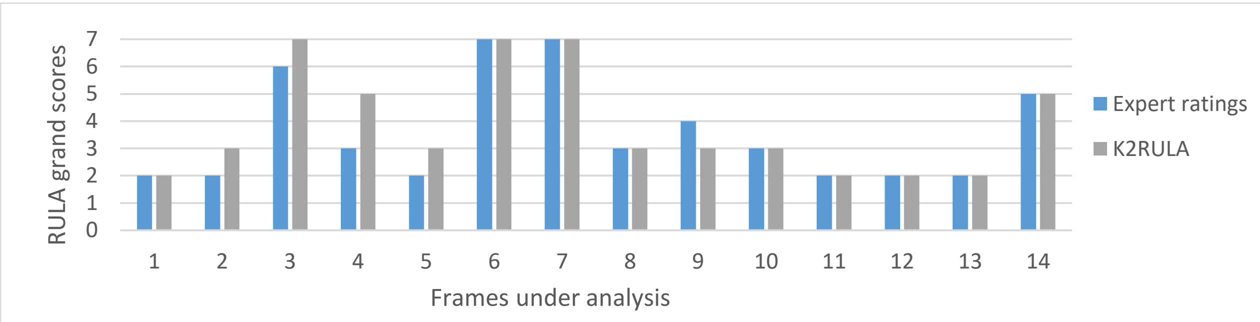

Figure 11: Expert and K2RULA ratings for the 14 frames under analysis.

We rated the agreement of the K2RULA tool with respect to the expert's scores, as we did in the experiment 1 (Table III).

Table III: Observed agreements, linear weighted Cohen's kappa and Z-test results

Methods	**Po**	**Cohen's kappa**	**Agreement scale (Landis and Koch)**	**z (k/sqrt(var))**	**p value**	**Null hypothesis**
Expert- K2RULA	0.93	0.79	Substantial	3.58	0.0003	Reject

4. Discussion

In experiment 1, for static postures, the KB methods reported exactly the expert grand scores for postures one, four, seven, eight, ten, and fourteen (Figure 10). In posture two, Jack-TAT underestimated the ergonomic risk, returning a low score for the neck. Analyzing the video frame, the neck appears back flexed, indeed this is a natural body behavior when rising up both arms as in this posture. 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 score. Jack-TAT gave a lower 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 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 the score correspondence is just accidental as it underestimates the arm section and overestimates the neck section. In posture eleven, the trunk is highly flexed forward. Our tool returned the highest 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.

We can affirm that Jack-TAT seems to underestimate the ergonomic risk returning frequently a grand score lower than the one estimated by the expert (mean error ε= -0.933, error std. dev. σ= 1.34). K2RULA slightly overestimates the risk (mean error ε = 0.267, error std. dev. σ = 0.44). This behavior is mostly due to an erroneous detection of raised shoulder. However, this overestimation is prudential, considering the motivation and the goal of this tool, i.e. a simplified method in the early stage of the analysis to highlight critical conditions for additional deeper investigation. The statistical comparison shows a better agreement between the K2RULA and the expert than the agreement between the Jack-TAT and the expert. Based on the results of experiment 1, we can state that:

- K2RULA represents a reliable method to assess RULA scores;
- K2RULA outperforms the Jack-TAT tool.

Also in the experiment 2, the analysis on the continuous movements confirmed the good agreement between the K2RULA and the expert. The proportion agreement index (p_0), and the linear weighted Cohen's kappa were similar to the ones from experiment 1 (Table III). The ergonomic risk was slightly overestimated (mean error ε = 0.286, error std. dev. σ = 0.70). One of the major limits of the score assessment resides in the evaluation of the wrist adduction/abduction angle. Thus, in the second, in the fourth, and in the fifth frames under analysis, we observed an overestimation of the wrist score with respect the expert rating. In the third frame, we had an erroneous detection of the raised state for the left shoulder. In the ninth instant only the expert could detect the neck twisting state, thus the K2RULA underestimated the risk. The hand configuration plays a key role in ergonomics, thus we will address our future research to overcome 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 ones. At the same time we, believe that filtering skeleton tracking data with a reliable digital human model could improve the reliability of metrics assessment. The availability of such data would further push towards the use of these monitoring systems, and would allow the implementation of tools able to assess fatigue indexes more detailed than the RULA score, such as OCRA index, moving from static postures analysis to continuous measurement.

Differently from Jack-TAT, K2RULA allows the offline analysis on recorded files. This feature, according to the authors, is very important to use the tool in the early stage analysis of the risk of exposure to WMSDs. Furthermore, it can be used as a training tool for non-expert ergonomic raters, whose RULA scores often suffer from high inter-observer variability. Nevertheless, its usage in real working environment should undertake further investigations. Indeed, we tested our tool in an experimental set-up with the subject under observation facing the sensor, without objects occluding field of view. This is the best working condition for the Skeleton Tracking algorithm for Kinect v2 (Wang et al., 2015) and Kinect v1 (Microsoft, 2013). Therefore, our results suffer only from the body joints self-occlusions and we need to investigate further the behavior of our tool in a real working environment. At the same time, it would be useful to evaluate how variation in the orientation of the tracking device affects the metrics-specific assessment.

We evaluated the reliability of our tool using as baseline the human expert scores, since the inter-rater variability of the RULA scores is low for expert raters (Robertson et al., 2009). It would be interesting to compare the performances of our tool with respect to those of expert raters using as golden standard the scores assessed with data gathered by an opto-tracking system.

The authors consider these results original and significant. Literature does not report any comparison between the first and the second version of the Kinect with respect to the assessment of ergonomic metrics. Moreover, as far as the authors know, there is no application of Kinect v2 for the assessment of the ergonomic risks in working activities.

The achieved results support the choice to address the research towards the implementation of automatic monitoring tools, able to support continuous monitoring and to give a real-time feedback to the operator.

The developed software prototype and the results obtained

5. Conclusions

In this paper, we investigated the use of Kinect v2 in RULA assessment. We developed and presented K2RULA, a software tool for speeding-up the screening process with an automatic and real time detection of critical conditions while avoiding the bias introduced by subjective observations. We compared the proposed tool with the traditional visual RULA inspection and with a commercial software, the Jack-TAT, based on the Kinect v1 sensor. The traditional visual RULA expert evaluation was our baseline. We evaluated the agreement of K2RULA scores with the expert ratings finding a statistical perfect match according to the Landis and Koch scale. K2RULA is able to detect critical conditions in real time. It is also able to analyze off-line data and to save the results for deeper ergonomic studies. In our tests, K2RULA outperformed Jack-TAT. A limit in our tests was the controlled setup. We will further investigate the behavior of the proposed tool in a real working environment. We will also evaluate how occlusions of the field of view due to objects, and the position of the sensor with respect to the worker, influence the skeleton tracking performances.

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