Ergonomics Measurements using Kinect with a Pose Correction Framework

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Abstract

Evaluation of potential risks of musculoskeletal disorders in real workstations is challenging as the environment is cluttered, which makes it difficult to correctly and accurately assess the pose of a worker. Being marker-free and calibration-free, Microsoft Kinect is a promising device to assess these poses, but it can deliver unreliable poses especially when occlusions occur. To overcome this problem, we propose to detect badly recognized body parts and to replace them by an appropriate combination of example poses gathered in a pre-recorded pose. The main contribution of this work is to organize the database as a filtered pose graph structure that enables the system to select relevant candidates for the combination: candidates that ensure continuity with the previous pose and similarity with the available reliable information. We applied the proposed method in a realistic environment that involved sub-optimal Kinect placement and several types of occlusions. An optoelectronic motion capture system was concurrently used to obtain ground truth joint angles. In an ergonomics context, we also computed Rapid Upper Limb Assessment RULA scores. This kind of ergonomics tool requires to rate the pose of the worker based on an estimation of the joint angles. These latter are then used to provide a global risk score. Results showed that when occlusions occur, the inaccurate raw Kinect data could be significantly improved using our correction method, leading to acceptable joint angles. As RULA calculation is based on angular thresholds, which tends to minimize the effect of joint angle errors, when these error values are not close to thresholds. However, for realistic scenarios with occlusions that lead to very large joint angle errors, the correction method also provided significantly better RULA scores. Our method opens new perspectives to define new fatigue or solicitation indexes based on continuous measurement contrary to classical static images used in ergonomics. As the computation time is very low, it also enables real-time feedback and interaction with the operator.

Keywords: Kinect, Pose correction, RULA Grid, Occlusions

1. Introduction

Microsoft Kinect is nowadays widely used to measure performance of a user in various application domains. Initially designed for video games, such a low-cost and easy-to-use motion capture device has been applied in clinical gait analysis (Auvinet et al. 2012; Auvinet et al. 2014; Galna et al. 2014), human-computer interactions (Wang et al. 2013), sign-language analysis (Gameiro et al. 2014; Pedersoli et al. 2014), sport training (Cassola et al. 2014) and ergonomics (Diego-Mas and Alcaide-Marzal 2014; Vignais et al. 2013). In ergonomics, posture and movement of the worker are important information for determining the risk of musculoskeletal injury in the workplace (Vieira and Kumar 2004). Consequently, several works have proposed assessment grids based on body posture, such as the famous RULA grid (McAtamney and Corlett 1993). This kind of ergonomics tool requires to rate the pose of the worker based on an estimation of the joint angles. These latter are then used to provide a global risk score. Recent works in ergonomics (Vignais et al. 2013) have demonstrated that real-time ergonomic feedback through Head Mounted Display positively influences the motion of workers decreasing locally hazardous RULA values. However, the method was based on inertial sensors and feedback devices that can change the way people perform the motion. Optical motion capture systems

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require positioning sensors or markers on the body and calibrating the system and the skeleton, which is not always possible in real work conditions. Indeed, sensors can be incompatible with security constraints and can also be perturbed by electromagnetic environment. These motion capture problems are also encountered in other application domain such as sports, training or rehabilitation.

Recent papers evaluated the accuracy of the Kinect skeleton data mostly for very simple motions and in accordance with the Kinect recommendation (sensor placed in front of the subject) (Clark et al. 2012; Kurillo et al. 2013; Bonnechère et al. 2014). It has been shown that this error rapidly increases for complex motions with auto-occlusions and when the sensor is not placed in the recommended position (Plantard et al. 2015).

Several methods have been proposed to correct baldy reconstructed poses provided by the Kinect. Since human motion is highly non-linear, learning statistical dynamic models (based on database of examples) as a motion prior can produce higher quality movements (Chai et al. 2007). Applying these methods to reconstruct Kinect poses has a major drawback as each body joint position is assumed to be accurately reconstructed whereas Kinect data deliver noisy or even incorrect information. To overcome this limitation, recent works have proposed to take the reliability of the Kinect data into account in the correction process. Reliability can then be integrated into a lazy learning framework to reconstruct a more reliable pose (Shum et al. 2013, Liu et al. 2014).

However, these methods have not been adapted and tested in constrained conditions, with many occlusions and poor sensor placement. In this paper, we propose a new method inspired by this example-based correction approach by introducing a new motion data structure to model the database of examples. The resulting structure, named Filtered Pose Graph, enables us to efficiently preselect a relevant subset of poses before correction, ensuring continuity and maximizing reliability even when important occlusions occur. This enhances both computation speed and reconstruction quality of the system.

The main contributions of the paper are:

- a method to correct Kinect data and to compute RULA scores,
- an evaluation of the actual usability of this method in constrained environments, in an ergonomic perspective.

The paper is organized as follows. The method used in this paper to improve the quality of Kinect data is presented in section 2. The computation of the RULA grid and the protocol used for the reliability evaluation of our method are given in section 3. Results about the joint angles evaluation and the RULA score estimation in constrained environments is given in section 4, and discussed in section 5.

2. Correction framework

The correction method improves the quality of Kinect data thanks to an example-based approach. The correction framework is composed of an offline and an online process as shown in Figure 1. The offline and the online part are described in the sub section 2.1 and 2.2 respectively.

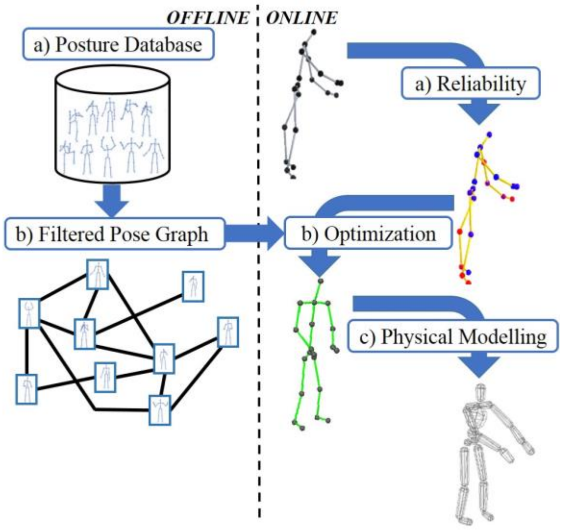

Figure 1: Overview of the pose correction method inspired by Shum et al. (2013). Offline database preprocessing: a) Posture database to b) Filtered Graph representation. Online pose correction: a) Reliability estimation, b) pose optimization and c) Physical filtering.

2.1. Offline

The offline process organizes the database of poses extracted from motion capture clips to produce a so-called Filtered Pose Graph (a and b in the offline part in Figure 1). The Filtered Pose Graph is a graph in which nodes are individual poses and edges are potential links between the two poses if they could be connected without discontinuities (i.e. distance between poses is below a given threshold). The graph is filtered to eliminate redundant poses and avoid creating an too-dense graph with numerous edges and nodes. The resulting graph enables us to rapidly select poses that are close to a given current pose, which could be considered as potential next poses in the studied motion. Hence, in the online correction phase, the idea is to rapidly gather this set of pose examples that could help to correct badly reconstructed body parts.

2.2. Online

The online correction process involves three steps. It first estimates the reliability of each joint center reconstructed by the Kinect (Figure 1.a). Then, based on the reliable information delivered by the Kinect, it selects the potential nodes (i.e. pose examples) in the Filtered Pose Graph that can help to correct unreliable joint positions. The resulting pose examples are combined using an optimization

process to replace unreliable information by plausible combined one while preserving continuity and similarity to the reliable information (Figure 1.b). Finally, a physical model is used to filter the resulted pose and avoid jerky motions (Figure 1.c).
For the first step, reliability of Kinect joint is computed with the method described in (Shum et al. 2013) which provides a reliable value between 0 and 1 for each joint.
In the second step, the unreliable part of the Kinect pose is corrected using a local optimization process. Firstly, the method selects the pose candidates that are relevant with respect to the reliable Kinect information in the Filtered Pose Graph. The Filtered Pose Graph allowed us to use large database while maintaining good real time performance during this online candidate selection. Moreover, selecting poses connected to the current one helps us to consider only candidates that ensures continuity with the current pose, while unorganized databases cannot guarantee continuity.
Then, a combined pose is obtained by minimizing a set of energy functions in an optimisation process. More precisely, optimization aims at finding the most appropriate weights used to linearly combine a set of pose candidates while minimizing a set of constraints modelled as energy terms: 1) Minimizing the difference between the optimizing pose and the observed Kinect pose for the joints considered as reliable. 2) The style term minimizes the difference between the optimizing pose and the selected pose in the Filtered Pose Graph. 3) Avoiding changes in bone length when combining various joint centers positions. 4) Ensuring continuity to minimize high frequency jittery movements.
The optimization score is evaluated as a weighted sum of the energy terms. The optimization process continues until an optimal solution is found, or the number of iterations reaches a predefined limit.
In the last step we filter the optimized joint positions using a dynamic model to accurately maintain kinematics features such as segment lengths. Readers are referred to Shum et al. (2013) for more details.

3. Material and methods

This section describes the method and experimental protocol used to evaluate the method introduced above in ergonomic context.

3.1. Computation of the RULA grid

3.1.1 Introduction to RULA grid

In ergonomics, one of the most popular observational method is the Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett 1993). This tool requires to rate the pose of the worker based on an estimation of the upper-body joint angles. Each joint angle is associated with a joint score according to predefined range of angles. For example, the upper arm score ranges from 1 to 4 if the shoulder flexion is within [-20; +20], < -20 or within [20; 45], within [45; 90], or >90 respectively. The same type of threshold are applied to the other upper-body joints angles. This approach leads to a discretization of the score that may be less sensitive to noise than methods that are based on continuous scores. One has to notice that additional conditions can increase the local body part scores, such as when the shoulder is raised or the upper arm is abducted.
These scores are combined to provide a global risk score for the left and right body parts, ranging from 1 (posture is acceptable) to 7 (workstation requires investigation and changes immediately).

3.1.2 Computation of joint angles using the Kinect data

To use the RULA method, relevant joint angles have to be computed based on the Kinect skeleton data (see Figure 2). A Kinect pose is defined as $p = \{x_j, y_j, z_j\}_{j=1..N}$ where N stands for the number of joints in the pose, and x_j, y_j, z_j stand for the 3D Cartesian coordinates of the j^{th} joint. According to the estimated joint positions, joint angles should be computed using the ISB recommendation (Wu et al. 2002, Wu et al. 2005). However, the Kinect skeleton is not fully compatible with this recommendation as it does not provide all the required anatomical landmarks.
We consequently slightly adapted the joint angle definition to take the available Kinect joints (maned with letters in Figure 2 a)) into account.

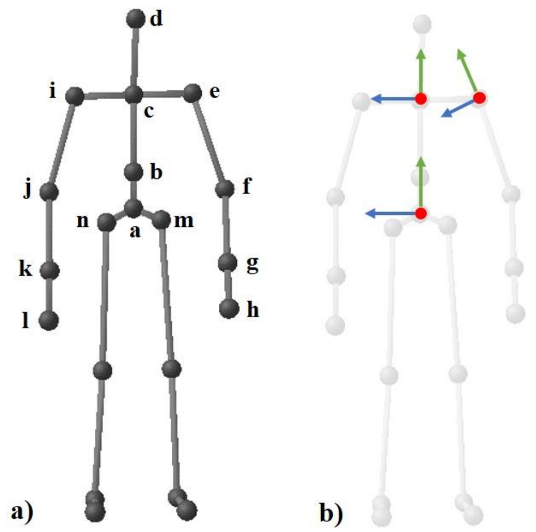

Figure 2: a) Skeleton model provided by the Kinect and the correction method. (a) hip center, (b) spine, (c) shoulder center, (d) head, (e) left and (i) right shoulders, (f) left and (j) right elbows, (g) left and (k) right wrists, (h) left and (l) right hands, (m) left and (n) right hips. b) Body part coordinates (pelvic, trunk and shoulder). X-axis in red pointing forward, Y-axis in green pointing upward and Z-axis in blue pointing to the right.

The pelvis coordinate is define relatively to the recommendation (Wu and al. 2002). Y-axis is along the trunk axes represented by the vector from the hip center (a) to the spine (b). The X-axis is defined as the normal of the plan formed by the Y-axis, the left (m) and the right (n) hips. Finally the Z-axis is computed as the normal of the X-axis and Y-axis.
For the trunk coordinate system, the Y-axis is represented by the vector from the spine joint (b) to the shoulder center joint (c). The X-axis is defined as the normal of the plan formed by the Y-axis, the left (e) and the right (i) shoulders. Finally the Z-axis is computed as the normal of the X-axis and Y-axis.
The shoulder coordinate system is defined according to the ISB recommendation. The Y-axis is given by the vector from elbow joint (f or j) to shoulder joint (e or i). The Z-axis is the normal of the plan formed by the Y-axis and the lower arm defined from wrist joint (g or k) to elbow joint (f or j). The X-axis is the normal of the plane formed by the two previous axis.
These three coordinate systems were placed to the hip center (a), shoulder center (c) and shoulder joints (e or i) respectively, as depicted in Figure 2 b).
The trunk and shoulder joint angles were then computed according to the ISB recommendation. We changed the matrix decomposition sequences of the shoulder joint angle computation from YXY to ZXY, to obtain abduction values and to limit gimbal lock problems as suggested in (Senk and Chèze 2006).
The Kinect skeleton also does not provide enough points to compute the neck and elbow local coordinate systems. We alternatively computed the elbow joint angles using the vector convention detailed by (Bonnechère et al. 2014).
The neck joint angles were computed by planar projection of the neck vector (c to d) expressed into the local trunk coordinate system.
As there is not enough available information to compute the wrist angles, the wrist, and wrist twist RULA scores are set manually. Finally, all the threshold values that are not provided by the RULA method are set to 20°, such as (Aptel et al. 2000) for the shoulder joint abduction.

3.2. Experimental set-up

In this section, we present the experimental protocol used to evaluate the relevance of the proposed method in constrained conditions, such as work conditions. To this end, we carried-out an experimental protocol with 12 male participants (age: 30.1±7.0 years, height: 1.75±0.046 m, mass: 62.2±7 kg). They were equipped with 47 reflective markers positioned at standardized anatomical landmarks, as suggested in (Wu et al. 2005). The motion of the participants was recorded by both Microsoft Kinect 2 sensor and 15 cameras Vicon optical motion capture system.
The subject had to perform getting and putting motions. More precisely, the subject had to carry a 40 cm per 30 cm per 17 cm box with the two hands, place it in front of the abdomen, wait few seconds and put it back to the original position. The box (attached to a magnet) had two target placements, in order to generate two different motions. The first placement named F (i.e. Front) the target was located in front of the subject, at 1.70 m high, 0.35 m left and 0.50 m in front. In the second placement S (i.e. Side) the target was located on the left of the subject, aligned with the two shoulders at the same height and 0.55m left.
To simulate workplace environmental constraints, three experimental setups were defined, including manipulation box (to add occlusions during the manipulation task) and various Kinect placements:

- [NB – No Box condition]: the manipulation of the box was simulated by the subject without using actually a box to avoid occlusions. The Kinect was placed in front of the subjects, as recommended by Microsoft. It enabled us to test the robustness of the Kinect sensor under favourable conditions. In this condition, the subject simply reached to the position of the attachment where the box would usually be located.
- [B – Box]: the manipulation is actually preformed with the box to created occlusions of parts of the body, as in real working situation. The Kinect was again placed in front of the subject, as recommended by Microsoft.
- [B45 – Box and 45° sensor placement] As in the B condition the subject actually manipulated the box but the Kinect was placed 45° left forward of the subject, as in real cluttered environments. In this condition, occlusion was more important.

The subject repeated each gesture 5 times: getting, and putting, for each conditions and box placement (F_{NB}, F_{B45}, F_B, S_{NB}, S_{B45} and S_B): 5 × 3 × 2 = 30 motions were recorded for each subject.
In this experimentation, the correction was performed using a Filtered Motion Graph made-up with 130 professional example gestures leading to 532,624 poses. The poses were then filtered into 2,048 nodes with an average of almost 7.81 links per node. The filtration intensity was chosen relative to the optimal condition used in (Shum et al. 2013).

4. Results

Firstly, we evaluated the accuracy of the joint angles measured with raw Kinect data or corrected ones, as these angles were used in RULA. To this end, we computed the root mean square error (RMSE) between the joint angles measured with the reference Vicon motion capture system, and those computed with the raw and corrected Kinect data, as described in section 3.1.2. This RMSE has been applied to the 8 main angles used in the RULA score: α_T, γ_T, for the torso, $\alpha_{LS/RS}$, $\beta_{LS/RS}$ for the left/right shoulders, and $\alpha_{LE/RE}$ for the left/right elbow flexion. Table 1 reports the joint angles ranges for all the joint angles and all the conditions, obtained with reference Vicon data.

Table 1: Joint angle ranges for the 6 scenarios in degree.

	F_{NB}	F_{B45}	F_B	S_{NB}	S_{B45}	S_B
α_T	11.4	12.6	13.2	7.4	5.8	6.1
γ_T	19.2	19.0	18.2	33.0	29.0	29.4
α_{LS}	130.8	104.6	108.6	111.5	93.5	90.9
β_{LS}	47.1	37.7	38.7	57.0	56.8	55.0
α_{LE}	76.8	67.9	67.4	85.9	71.9	74.5
α_{RS}	125.4	99.3	99.5	111.9	83.8	85.8
β_{RS}	30.7	25.1	24.3	38.7	36.8	35.8
α_{RE}	73.9	69.0	68.4	83.1	73.9	75.5

One can see that some angles exhibit very low ranges, such as the trunk flexion α_T, whereas other vary in a wider range, such as the shoulder flexion α_{LS}. Consequently, displaying RMSE in a unique figure for all the joint angles may be difficult to analyse. Thus, to have a synthetic view of all the results in a unique figure, we normalized the RMSE by the range of angles reported in Table 1:

$$nRMSE(\theta_i) = \frac{RMSE(\theta_i)}{\max(\theta_i) - \min(\theta_i)}$$

The resulting synthetic figure is given in Figure 3 for the 8 main angles (one star diagram per type of trial). The results exhibit the nRMSE between 0 (no error) to 1 (error corresponding to the range of motion). It is displayed for the 6 studied conditions. Kolmogorov-Smirnov test was used to check the normality of the distribution of the nRMSE for this analysis. The distributions did not follow a normal law. A Wilcoxon signed rank test was used for detect significant differences between Kinect error and corrected error for all the subject in each condition.
In this Figure, no-occlusion scenarios (F_{NB} and S_{NB}) exhibit lower errors compared to those involving partial occlusion (F_{B45}, S_{B45}, F_B and S_B). In no-occlusion scenarios, correction of Kinect data did not significantly decrease this error. On the opposite, when occlusions occurred, corrected Kinect data leads to significantly ($p < 0.001$) better estimation of joint angles compared to reference Vicon data.
For scenario FB (displacing a box), nRMSE reached higher values than 1 for two torso angles: α_T and γ_T. This is mainly due to the fact that the joint angles varied in small ranges while occlusions due to the box leaded to high errors when using a Kinect placed in front.

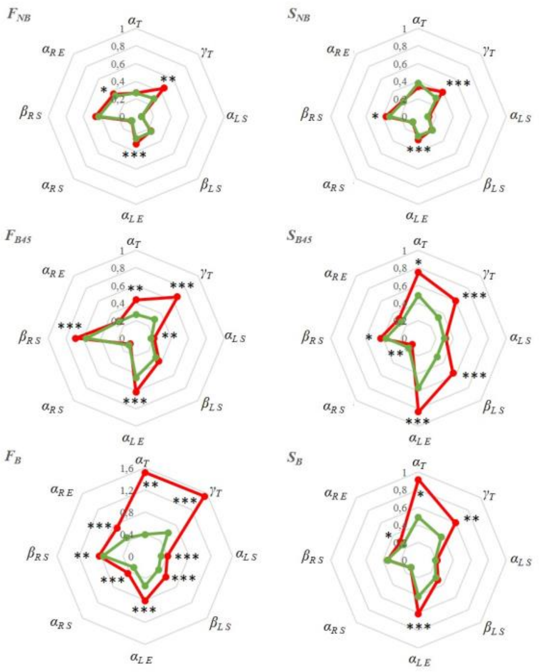

Figure 3: Normalized RMSE between reference angles using the Vicon data and using both raw Kinect (in red) and corrected Kinect (in green), for the 6 situations.

Secondly, based on the joint angles computed with the raw and corrected Kinect data, we computed the corresponding RULA score, as described in section 3.1. In the same way, we computed the RMSE between the RULA score computed using the reference Vicon data and the two Kinect ones. Let us recall here that the RULA score ranges from 1 to 7 only for each body side. The results are reported in Table 2. Significant difference between the RMSE is noticed with *, **, and *** for $p < 0.05$, $p < 0.01$ and $p < 0.001$ respectively.

Table 2: RMSE between the reference RULA score computed with Vicon data compared to using direct or corrected Kinect measurements. Significance between the two performances is given by *** for p < 0:001.

	RULA Left			RULA Right		
Motion	Kinect	Correct	*p*	Kinect	Correct	*p*
F_{NB}	0.49	0.50	NS	0.45	0.41	*
F_{B45}	0.66	0.65	NS	0.66	0.55	***
F_B	1.30	0.63	***	1.40	0.49	***
S_{NB}	0.55	0.63	*	0.65	0.62	**
S_{B45}	0.59	0.60	NS	0.62	0.45	***
S_B	0.51	0.51	NS	0.42	0.36	**

In this table, one can see that the average error is below 1 for most of the scenarios, except FB where occlusions with the box occurred. For scenarios with occlusions, frequently observed in real workstations, the correction method provides significantly better angles and RULA scores.

As RULA is based on angular thresholds, it tends to minimize the effect of noise when the angle is far from the thresholds. Hence, it leads to more acceptable errors than simply looking at the joint angles. However, in a multimedia interface delivering real-time feedback to a user about his RULA performance, this could be a problem. Indeed, if the user can visualize an avatar with a badly reconstructed pose, different from his actual performance, he may not be able to understand and adapt his performance to decrease the RULA score. In this type of real-time feedback system (Vignais et al. 2013), the coherence between the user's motion, the avatar pose and the RULA score is very important. In most of no-occlusion scenarios we could expect to have acceptable results. This statement could be confirmed by carrying-out perceptual studies.

Table 3: Percentage of correctly computed RULA score for the left and right body parts, using the direct Kinect measurement or the corrected one. Significance between the two performances is given by *** for p < 0.001

	RULA Left			RULA Right		
Motion	Kinect	Correct	*p*	Kinect	Correct	*p*
F_{NB}	77	75	NS	80	82	*
F_{B45}	71	69	NS	62	75	***
F_{B}	52	69	***	55	79	***
S_{NB}	76	71	NS	76	78	**
S_{B45}	74	71	NS	64	80	***
S_{B}	78	77	NS	82	86	**

RMSE is based on averaged errors and it could be interesting to also analyse the performance of the Kinect correction to correctly compute the RULA score. To this end, Table 3 reports the percentage of correctly computed RULA scores (zero difference between the Vicon-based score and the Kinect-based scores) in all the conditions. For RULA scores based on raw Kinect data, this percentage is between 51% (most occluded condition) and 82% (few occlusions condition). In the worst case, with many occlusions, this percentage significantly raised from 52% (resp. 55%) to 69% (resp. 79%) for the left (resp. right) upper-limb.

The above analyses have been carried-out with the 6 controlled laboratory conditions. However, in real workstations the occlusion and camera placement may be much more important. Indeed, the sensor placement is highly constrained by the environment and many occlusions may occur, due to the objects which are manipulated. Consequently, as a proof of concept, we applied our method to two simulated workstations scenarios, involving the manipulation of a real car seat, as depicted in the Figure 4.

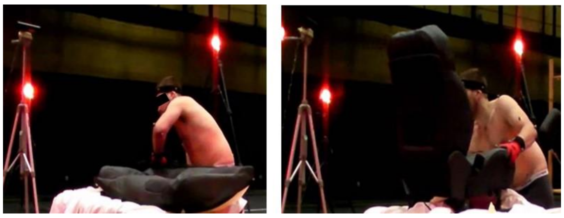

Figure 4: The two simulated workstations scenarios. (left) lightly occluded scenario. (right), heavily occluded scenario.

As shown in the Figure 4, the camera was not placed in the position recommended by Microsoft. The first scenario involved light occlusion, whereas heavy occlusion occurred in the second one. The Vicon system was also placed in the environment to measure reference data, as for the previous controlled conditions.

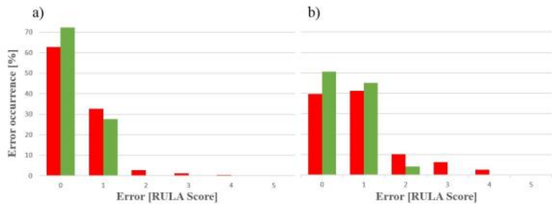

Figure 5: Histogram showing the percentage of frames for which the RULA score error is 0, 1...5 when using raw (red) and corrected (green) Kinect data. Two realistic scenarios are studied: a) simple one with few occlusions, b) complex one with many occlusions.

Figure 5 depicts the histogram of the RULA score errors when using raw and corrected Kinect data: the percentage of images where the error was equal to 0, 1, 2, 3, 4 and 5. These results show that almost all the errors greater than 1 disappeared when using the corrected data instead of raw Kinect data. As expected, the second scenario with many occlusions (Figure 5.b) exhibits lower occurrence of 0-error images compared to the first scenario (Figure 5.a). However, correction of Kinect data enabled us to eliminate almost all the errors greater than 1, while it corresponded to almost 20% of the cases without correction.

To summarize, results reported in this paper are promising for the ergonomic evaluation of workstations in real environments, using standard measurement methods. The current framework shows a practical capacity to correctly provide ergonomics evluation for working tasks with a cheap and easy-to-use system. Figure 6 depicts an example of potiential application based on our framework, where joint angles and resulting RULA score are given to the ergonomists. The user can visualize the video, the 3D character, joint angles, and RULA scores for each frame of the recording, at 30Hz. It provides supplementary temporal information, such as the time spent above a given RULA score.

Figure 6: Example of ergonomics application based on our Kinect data correction framework.

5. Discussion

The results showed correction of Kinect data allowed us a significant improvement of the joint angle accuracy, particularly when the body was partially occluded. RULA score was more reliable with corrected data, although angular thresholds tended to minimize the effect of noise when using Kinect raw data.

The skeleton delivered by the Kinect did not contain all the required information to compute all the joint angles as accurately as using Vicon data with ISB recommendations. Particularly, Kinect delivered very noisy and unreliable information about the hand. Hand configuration is a key point in ergonomics, as reported in the RULA assessment scores. As it is not correctly measured by the Kinect most of the time, further research would be necessary to address this particular point. Hence, motion involving dexterous manipulation and fine motion of the wrist cannot be studied with such a system. The method used for correction involves that a minimum set of reliable information is delivered by the Kinect, which is not guaranteed for the wrist in Kinect v1 and v2.

Another limitation of the method is the use of a database that may not correspond to the actual use of the system. In this paper, we used a database trained with working motions, similar to those performed by the subject. For other type of motions, involving poses that have never been recorded before, especially for larger ranges of motions, the performance of the correction method would not be so good.

The method is also based on a set of parameters, such as the number of candidates used to run the optimization, or the thresholds applied to prune the database and eliminate redundant information. It would be interesting to evaluate the actual impact of these parameters on the performance of the correction method.

Despite the reported limitations, the results of the current study are promising for the ergonomic evaluation of workstations. Kinect has already been considered as a promising tool to evaluate ergonomics on-site (Diego-Mas et al. 2014; Patrizi et al. 2015), but only with very simple and inaccurate posture representation. This study shows the applicability of our framework for a wider use and global evaluation tool. Using such automatic system enables to deliver a score at each frame (30Hz with a Kinect), which is an improvement compared to traditional methods based on few key frames. Indeed it could provide the amount of time spent above a given score as an additional information for the ergonomist.

6. Conclusion

This paper presents an evaluation of the quality of angular and RULA score values when using a Kinect with software correction. The result showed that both corrected and uncorrected Kinect data enabled to compute acceptable to reliable angular and RULA score data in occlusion-free conditions. However, in more challenging environments with occlusions, kinematic data provided by the Kinect was more noisy, leading to inaccurate estimation of the joint angles. The proposed correction framework enables us to consider encumbered capture area (e.g. production chain) that leads to such occlusions or bad sensor placements. Uncorrected Kinect data exhibited much higher errors than corrected ones, which may lead to difficulties when using the system in real working environments.

Finally, one has to notice that correction runs in real time and allows the possibility to implement real-time user feedback, with potential application in training or virtual prototyping, as suggested by (Vignais et al. 2013).

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