A validation framework for predictive human models

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Abstract: A validation framework is introduced in this work to evaluate the motion of a predictive human model and provide feedback to the model developers for refinement in ergonomic applications. Two qualitative and two quantitative benchmark tests were designed and used to assess the strength and weakness of the model and to localise abnormalities in the predicted motion. Twelve subjects participated in a whole-body motion task, and another 12 subjects participated in the subjective evaluation of the predicted motion. The validation framework was able to highlight the weakness and limitations of a predicted human model with 55 degrees of freedom in a box-lifting task. The results have shown that the proposed framework was very effective in identifying the flaws in the model under investigation and in giving guides for improvement and acceptance.

Keywords: box lifting; quantitative; qualitative; whole-body; validation; predictive-human model; ergonomics; human factors; virtual interactive design; virtual experimentation.

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1 Introduction

Many biomechanical models have been developed to predict human biomechanics for real-life applications (Granata and Marras, 1993; Adams and Dolan, 1995; Chadwick and Nicol, 2000; Faber et al., 2007; Arjmand et al., 2009; Garg and Kapellusch, 2009; Waters and Garg, 2010). Those simulation algorithms in one way or another use motion supported by libraries of databases (Choi et al., 2003; Thelen and Anderson, 2006; Erdemir et al., 2007; Hoozemans et al., 2008; Burgess et al., 2009). Some approaches use predicted motions that are based on an optimisation problem formulated by defining appropriate performance measures and constraints to recover the real motion of a biomechanical system (Anderson and Pandy, 2001; Chevallereau and Aoustin, 2001; Gill et al., 2002; Mu and Wu, 2003; Saidouni and Bessonnet, 2003; Ren et al., 2007; Kim et al., 2008; Xiang et al., 2009a).

A validated predictive human model will open the door to conducting unlimited tests of various combinations of loads, motions, and body anthropometries for numerous ergonomics studies and will contribute considerably to the development of human biomechanics research. Approaches to validating predictive human-model motion (Marras and Sommerich, 1991; Blankevoort and Huiskes, 1996; Rabuffetti and Baroni, 1999; Karduna et al., 2001; Robert et al., 2007; Dubowsky et al., 2008; Abdoli-Eramaki et al., 2009; Chaffin, 2009) have been very effective in assisting the development and the acceptance of the models. Generally, most existing validation methodologies of computer human models are designed for specific usage/tasks and usually target a certain area of the human body or use a low-fidelity human model with a limited number of links and joints.

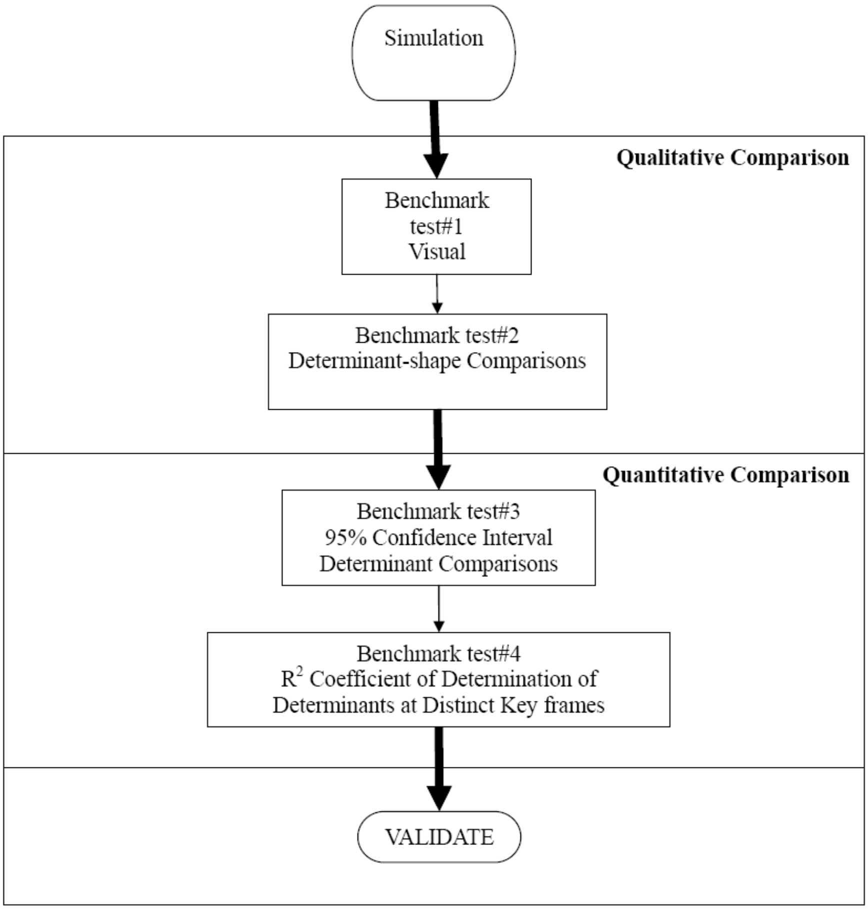
In the current work, a framework to validate the predicted motion of a whole-body task is introduced. The proposed validation framework is based on four benchmark tests to characterise the conditions under which the upper and lower body motions are considered acceptable. The first two benchmark tests are based on qualitative comparisons and are used to construct a general perception about the normality of the motion. Also, they act as checkpoints and signs for the model developers to either move forward through the following quantitative comparisons or go back to the work table and search for better prediction approaches. The last two benchmark tests are based on quantitative comparisons and provide critical and detailed information about the quality of the model in general and the weaknesses at specific local locations. The latter tests also impose tighter passing conditions for the model testing and improvement. In this work, the validation framework is applied to a box-lifting prediction model of a whole-body human computer model with a large number of degrees of freedom (DOF), and the corresponding results are presented.

2 Validation methodology

The proposed validation methodology involves testing the ability of predicted models to pass effectively and consecutively through four benchmark tests comprising two qualitative and two quantitative tests. In general, the benchmark tests depicted in Figure 1 are ordered in increasing levels of strictness of conformity and validation effort. During the first benchmark, subjects observe and compare movies simultaneously played back by two avatars. One avatar uses experimental data, and the second avatar uses predictive data. The second benchmark involves subjectively comparing the general shape of the joint angle time histories for the experimental and predicted avatars. The third and the fourth benchmarks quantitatively compare the joint angle time histories of selected joints that play major roles in the task based on statistical metrics. All benchmarks are considered valuable because substantial effort could be saved if the predicted motions could be configured during the early benchmark tests.

The proposed validation methodology performs each benchmark test by comparing the predicted motions against the average motions obtained by performing experiments for the same task. In order to compare the experimental and simulation results, the experimental 3D displacement data acquired by the motion capture system is first transformed from the Cartesian space to the joint space using a global optimisation-based inverse kinematics scheme (Lu and O’Connor, 1999). Due to the large amount of information in the resulting motion, the validation process becomes cumbersome. Therefore, the current validation methodology considers a subset of the full DOF set for the comparison. This subset is called task determinants (TD) and includes the joint angles that play a major role in accomplishing the task (Saunders et al., 1953; Hsiang et al., 1999; Lin et al., 1999). Furthermore, the validation methodology considers a more restrictive subspace of these TD at selected distinct key-frames (DKF) from the TD time history. The DKF represent the magnitude of the determinants at critical well-defined frames in the determinants’ time history, such as the magnitude of the knee angle at 0%, 20%, 40%, 60%, 80%, and 100% of the lifting height. In addition to validating the kinematics of the motion, the proposed validation methodology also checks the kinetics of the motion.

Figure 1 Flow chart of the validation framework represented by the four benchmark tests ordered in increasing level of strictness of conformity



2.1 Qualitative comparison

The objective of this early stage in the validation process is to assess the normality of the predicted motion in general subjective terms before proceeding to the more thorough detailed comparisons. This stage is composed of the first two benchmark tests (Figure 1). In the first benchmark test, 12 subjects observed two videos of a box-lifting task being performed by two similar virtual avatars; one video played back the results from predicted lifting motion and the other played back the results from the experimental lifting motion. The subjects had no knowledge regarding the identity of the avatars. Some of the subjects were familiar with the DHM, but most subjects were not. The subjects who were familiar with the model were non-technical people. The subjects evaluated the level of motion normality of the two videos by drawing a line crossing a straight line-scale ranging from abnormal to normal motion (Aitken, 1969). The subjects did not have the capacity to play with the software and watch the animation from different angles. This was done to minimise the differences in the subjects' performance due to their background and to have them focus on the motion only. The results of this stage elucidate whether or not the model reasonably simulates normal motion. This test provides information to the model developers to either proceed through the subsequent tighter benchmark tests or go back and refine the model at specified locations. At this stage, substantial time and effort were saved since the motion of only one subject was recorded to create the video. In the second qualitative benchmark, a relatively more detailed subjective comparison is conducted at the TD level. The comparison in this case was performed on the kinetics and kinematics of each predicted determinant and its derivatives. This is done by subjectively comparing the general shape of the predicted determinants with that of the normal determinants in the time domain. The results of this stage will reveal if there are major discrepancies between the model and the experimental determinants.

2.2 Quantitative comparison

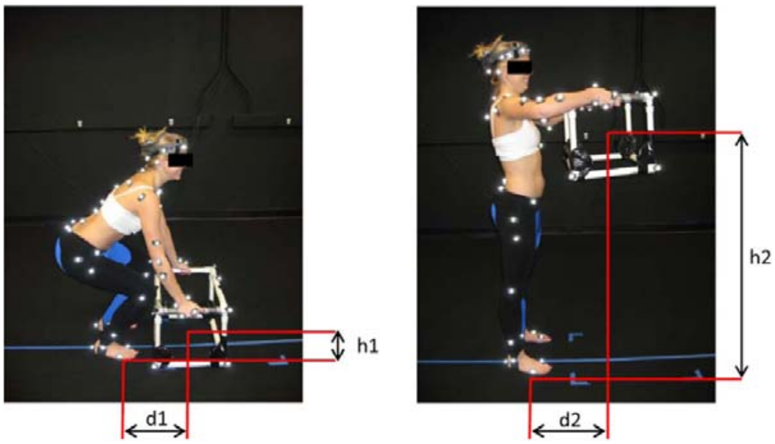
This stage includes the last two benchmark tests depicted in Figure 1. It comprises rigorous statistical comparisons between the magnitude of the predicted and normal lifting determinants. While the first qualitative stage presented in the previous section could include some unintentional bias, the current quantitative comparison stage requires tighter conditions and has less bias involved as the decision is made based on the database of the task under validation and the accuracy needed for a certain application. The first benchmark of this stage tests if the predicted time history magnitude of the TD follows the magnitude of the mean of the normal subjects and falls within the 95th percentile interval of confidence. The second and final benchmark of this stage is designed to statically determine, using the coefficient of determination R^2, the degree of correlation between the predicted and experimental TD at DKF.

2.3 Application to a predictive-lifting model

This section presents a brief description of a predictive model that is used in this work as an example to demonstrate the effectiveness of the proposed validation framework. The model predicts the motion of various joints and the ground reaction forces during the lifting by solving an optimisation problem. In this optimisation problem, both the motion and the forces that cause the motion are unknown and treated as design variables. The basic idea is to minimise an objective function such as the dynamic effort, which is defined as the time integral of the squares of all joint torques, subjected to physical constraints such as joint limits, torque limits, ground penetration, foot locations, and balance (Xiang et al., 2010).

In the current simulation, the symmetric lifting task is defined as moving a heavy box from an initial location to a final location. Figure 2 depicts the input parameters for the proposed formulation. In this regard, h_1 is the initial height of the box measured from the ground, d_1 is the initial distance measured from the ankle location to the centre of the box, h_2 is the final height measured from the ground, d_2 is the final distance, and w is the weight of the box. The predictive model under investigation predicts the motion of various joints and the ground reaction forces during the lifting.

Figure 2 Input parameters for the predicted lifting task (see online version for colours)



3 Method

3.1 *Participants*

Twelve subjects participated in the subjective evaluation of the predicted motion, and another 12 subjects participated in the testing of a whole-body motion task. The first 12 subjects were asked to watch movies of two avatars, one driven by simulation data and one driven by experimental data, and then to evaluate their motion normality. The second 12 subjects (eight healthy males and four healthy females) were involved in the experimentation of the materials-lifting task. The subjects had no history of musculoskeletal problems and were reasonably fit. Their participation was voluntary, and a written informed consent, as approved by the University of Iowa Institutional Review Board, was obtained prior to testing. The height of the subject population for the materials lifting task was 175.6 +/– 11.5 cm with a weight of 73.2 +/– 10.7 kg and age of 21.8 +/– 4.3 yrs.

3.2 *Experimental procedure*

3.2.1 *Lifting task description*

Subjects were instructed to stand in a neutral position, referred to as the T-pose (Figure 3), which corresponds to the initial joint angles and segment locations of the skeleton. The T18 pose is defined as standing with feet shoulder width apart and parallel, and with arms raised parallel to the floor in the transverse plane and lateral to the body in the frontal plane. Palms face forward with the elbows maximally extended and the olecranon process pointed towards the ground. It is well-known that subjects may use different lifting strategies depending on their strength and their perception of the load (Bartlett et al., 2007; Li and Zhang, 2009). In this work, participants were aware of the weight of the box (20 lb for males and 15 lb for females) and were shown proper material-lifting strategies to avoid any unexpected harmful strategy. They were then instructed to lift a box from the standing surface to shoulder height in their most natural or comfortable way (Burgess-Limerick et al., 1995). Adequate warm up and rest time was allotted.

Figure 3 A subject in a T-pose position (see online version for colours)

3.2.2 Measurements and data collection

Natural human motion was collected using a system of 16 infrared cameras (Motion Analysis Corporation, Santa Rosa, CA) with a peak capture rate of 200 Hz to track the motion of 53 passive reflective markers at 100 frames per second. Reflective markers were placed to highlight anatomical landmarks (Cappozzo et al., 1995; Della Croce et al., 1999).

Based on the literature (Saunders et al., 1953; Hsiang et al., 1999; Lin et al., 1999; Neumann et al., 2001) and a fair understanding of the lifting process, six determinants (trunk flexion, shoulder flexion, elbow flexion, hip flexion, knee flexion/extension, and ankle plantar/dorsiflexion) were identified as the major contributors to the overall box-lifting motion.

Predictive model results are expressed in terms of joint space; therefore, direct comparison becomes more convenient after transforming the experimental data from the Cartesian space to the joint space using inverse kinematics (IK) (Lu and O'Connor, 1999; Oyama et al., 2001; Roux et al., 2002; Wu et al., 2004; Nicolas et al., 2007; van den Bogert and Su, 2008).

3.2.3 Inverse kinematics

Due to the geometrical complexity of the current skeleton model and the involvement of the lower and upper body segments during the lifting process, the usage of commercial software, such as Vicon, Motion Analysis, and Visual3D, for the calculation of joint angles for direct comparison purposes with the predicted model is possible but becomes cumbersome at many DOF. This is because of the incompatibility between the commercial software model and the current skeleton model, not only in terms of the direction and orientation of the joint axes, but also in terms of the total number of joints, as well as the inability of these commercial software programmes to animate the current skeleton model using joint angles. To circumvent these problems, an in-house IK scheme is introduced to correlate the adjacent joint's local coordinate systems, based on the geometry of a skeleton similar to that of the model, and expressed by a DH table (Xiang et al., 2009a, 2009b). The ability to animate the current skeleton using joint angles is an essential component of the first stage of the proposed validation methodology. Due to the high degree of redundancy, a large-scale sequential quadratic programming (SQP) approach in SNOPT (Gill et al., 2002) was used inside the in-house IK to solve a global (considering the whole-body) optimisation problem subjected to the joint-limit constraints.

4 Results

4.1 Qualitative comparison

Twelve participants participated in the first benchmark test to observe and evaluate two videos of animated avatars. One avatar was animated using experimental data and the other was animated using predicted data. The participants were asked to report their scores based on what they consider a natural human lifting motion. Figure 4 shows a comparison of the rating scores for both avatars. The coefficient of correlation (r) between the experimental and simulation rate was 0.692729.

Figure 4 Subjective rating to the motion normality of two similar avatars; one is driven b simulation motion and the other is driven by experimental data

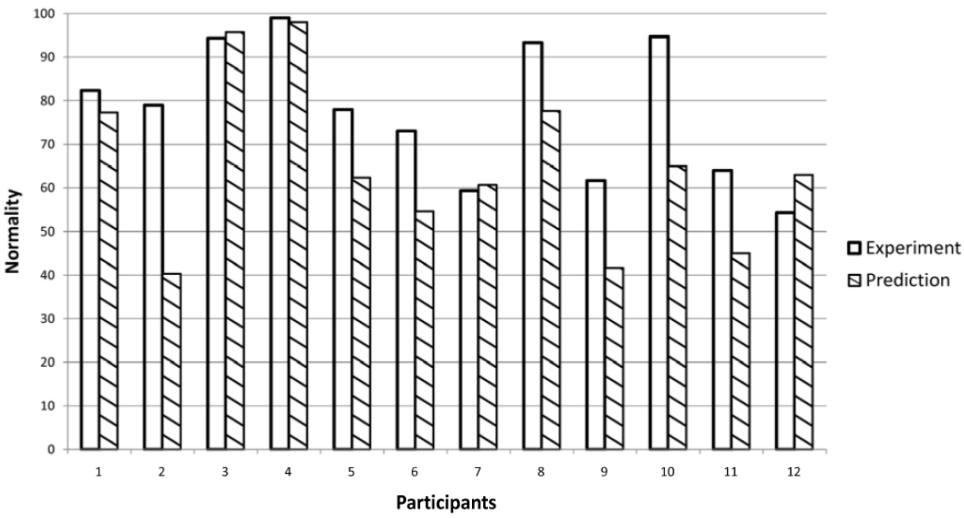
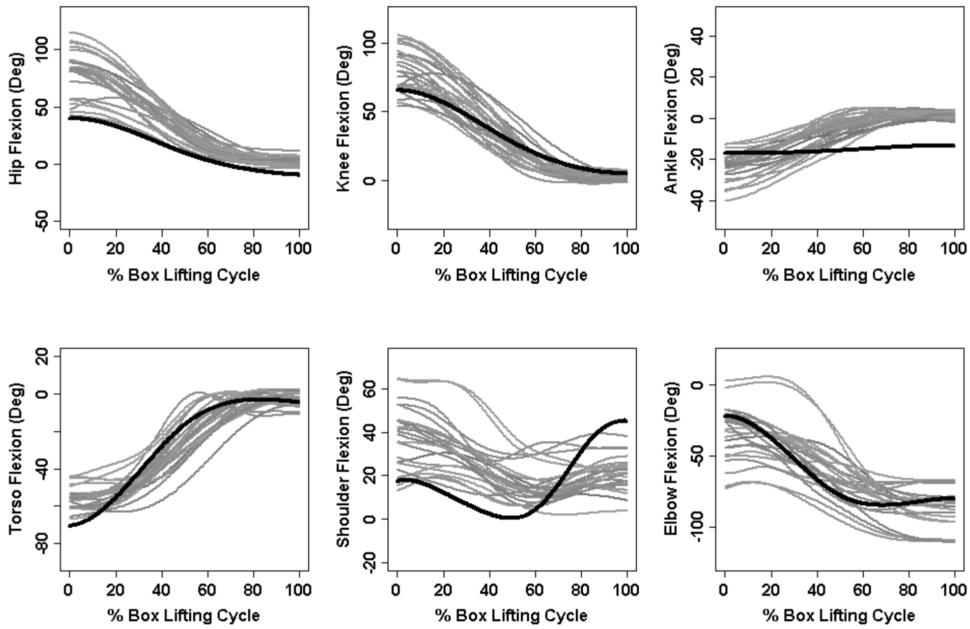
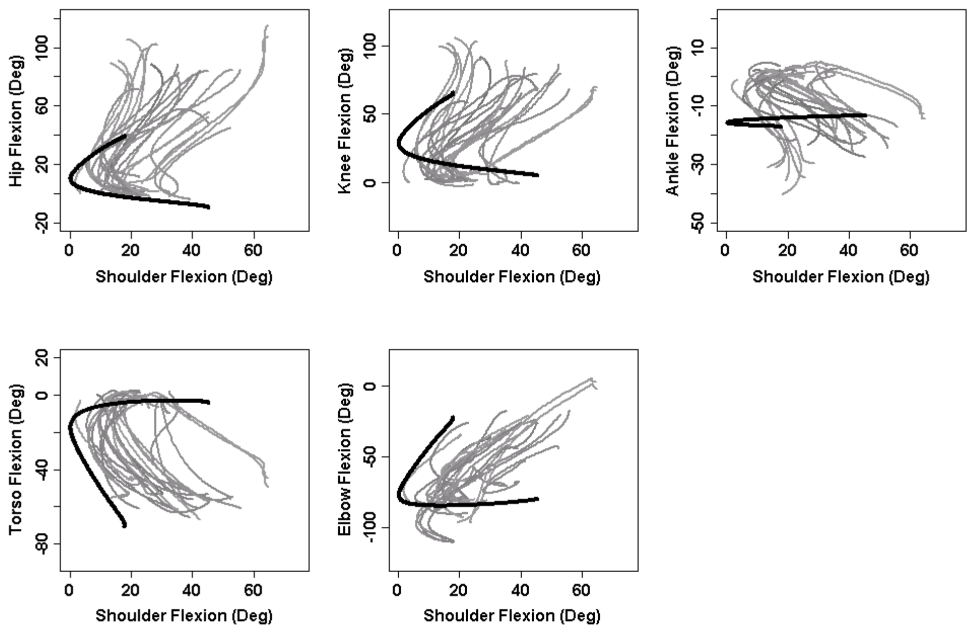


Figure 5 Box-lifting experimental results, (a) shapes of the lifting determinants (grey lines represent experiments while the dark-solid line represents prediction curves) (b) Coupling between the shoulder flexion motion with hip flexion, knee flexion, ankle flexion, trunk flexion, and elbow flexion during lifting

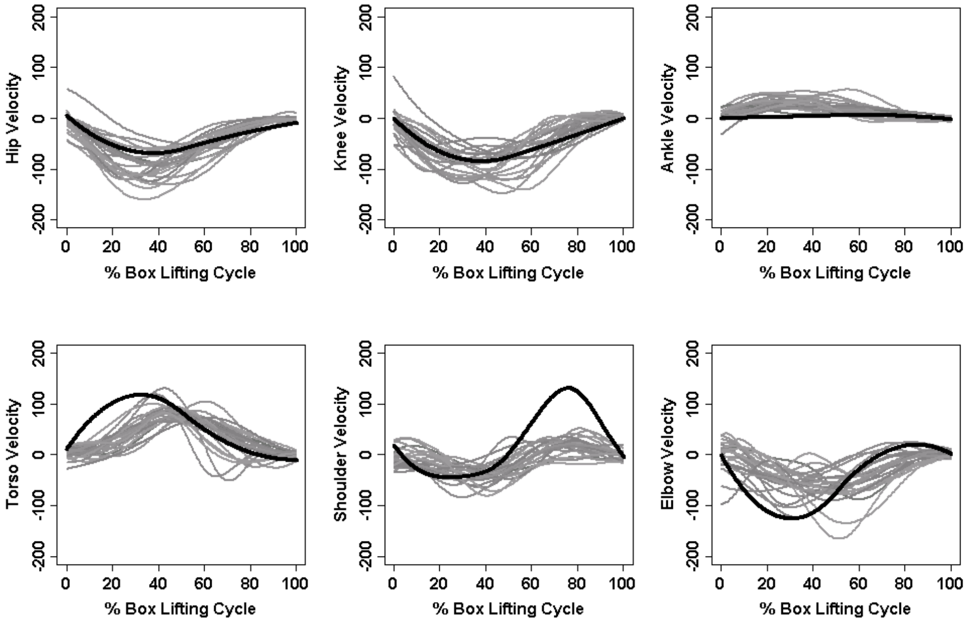


(a)

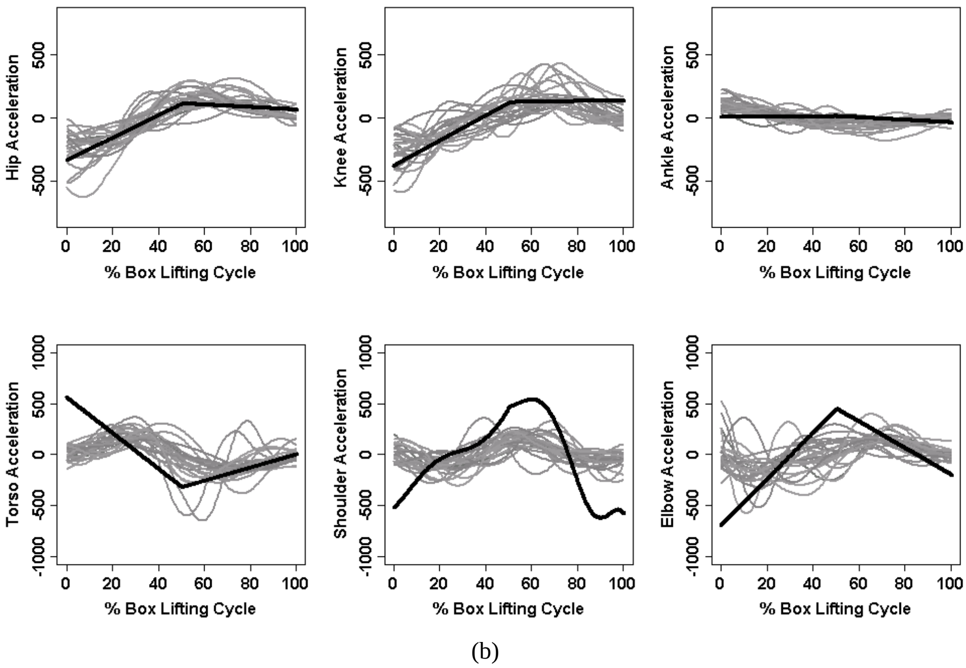


(b)

Figure 6 Comparison between (a) the velocity and (b) the acceleration of the box-lifting determinants of the 12 subjects and the predicted model



(a)

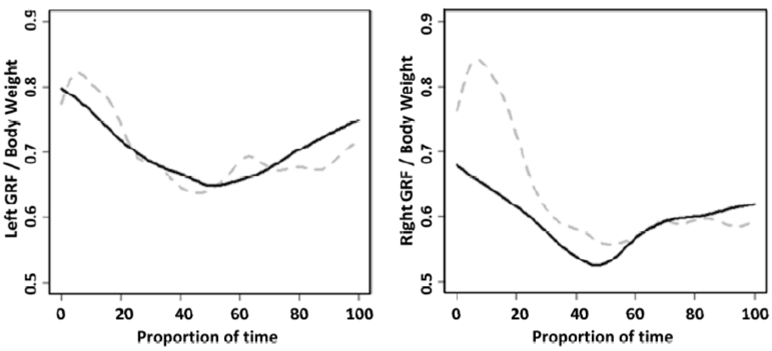


(b)

For the second benchmark, Figure 5(a) shows that the predicted determinant-curve shapes, except for the ankle flexion, for lifting during the lifting cycle have general shapes that closely followed the individual 12 subjects. Figure 5(b) demonstrates the coupling strength between one of the predicted determinants, shoulder flexion as an example, with other TD. As can be seen in the figure, the predicted shoulder flexion determinant has followed to some extent the trend of coupling between the determinants of the natural subjects. Again, the predicted ankle flexion showed weak correlation with the experiments.

Figure 6(a) demonstrates a comparison between the velocity of the lifting determinants of the 12 subjects and the model. As can be seen from the figure, the shape of the predicted model velocity is similar to that of the subjects for the torso and hip. However, there are fewer local fluctuations in the predicted TD. The shape of the rest of the determinants was somehow different. The calculated acceleration showed behaviour similar to that of the velocity as depicted in Figure 6(b); however, more local fluctuations appeared in the experimental curves. For kinetics, Figure 7 shows the experimental and predicted vertical and forward ground reaction forces during lifting. As can be seen from Figure 7, the predicted model showed behaviours similar to those of the experimental data but was not able to capture the initial characteristics of the lifting cycle.

Figure 7 Ground reaction forces in the vertical direction during the box-lifting cycle



Note: Dashed grey curve represents experimental results while solid dark curve represents the predicted results.

4.2 Quantitative comparison

The comparison between the experimental and the predicted TD in terms of the interval of confidence are presented in Figure 8. The experimental data for each subject represents the average of two lifting cycles. The model determinants show weak correlation for the ankle and the shoulder flexions; however, they show reasonable correlation and agreement with the human subjects for the rest of the determinants, by being inside the interval of confidence and following the trajectories of the subjects' determinants. Figure 9 depicts the R^2 plot for the six TD for the DKF shown in Figure 10. The circle shape in Figure 9 represents the relationship between the simulation data and the average experimental data of the hip flexion of 12 subjects. Other symbols represent the relation for the rest of the determinants.

Figure 8 95% confidence intervals of box-lifting determinants (region between the dashed lines), subjects' mean (solid grey line), and predictive model (solid dark line)

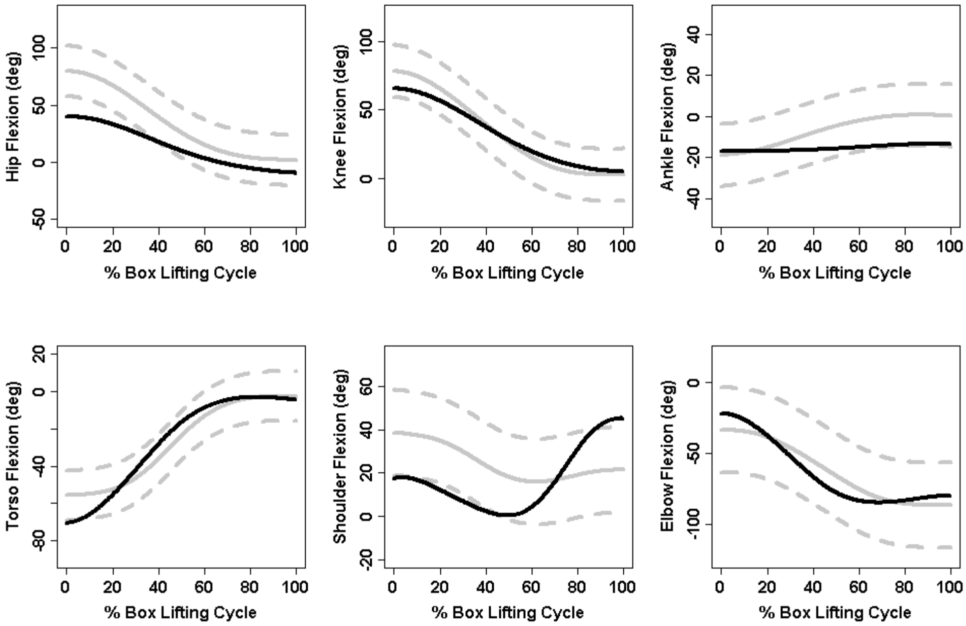


Figure 9 R^2 plot for the six lifting determinants at the six selected key-frames: the vertical axis (in degrees) stands for predicted data, and the horizontal axis (in degrees) corresponds to the average experimental data

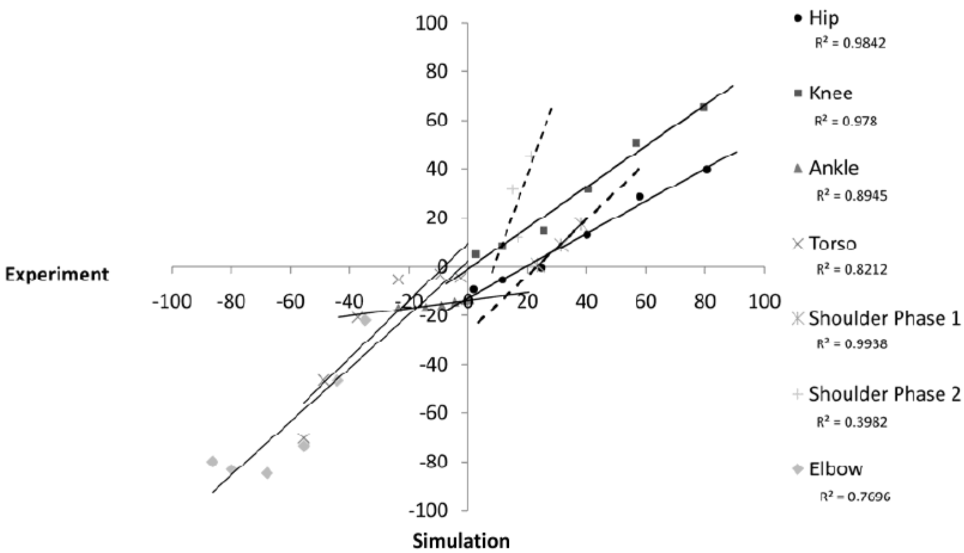
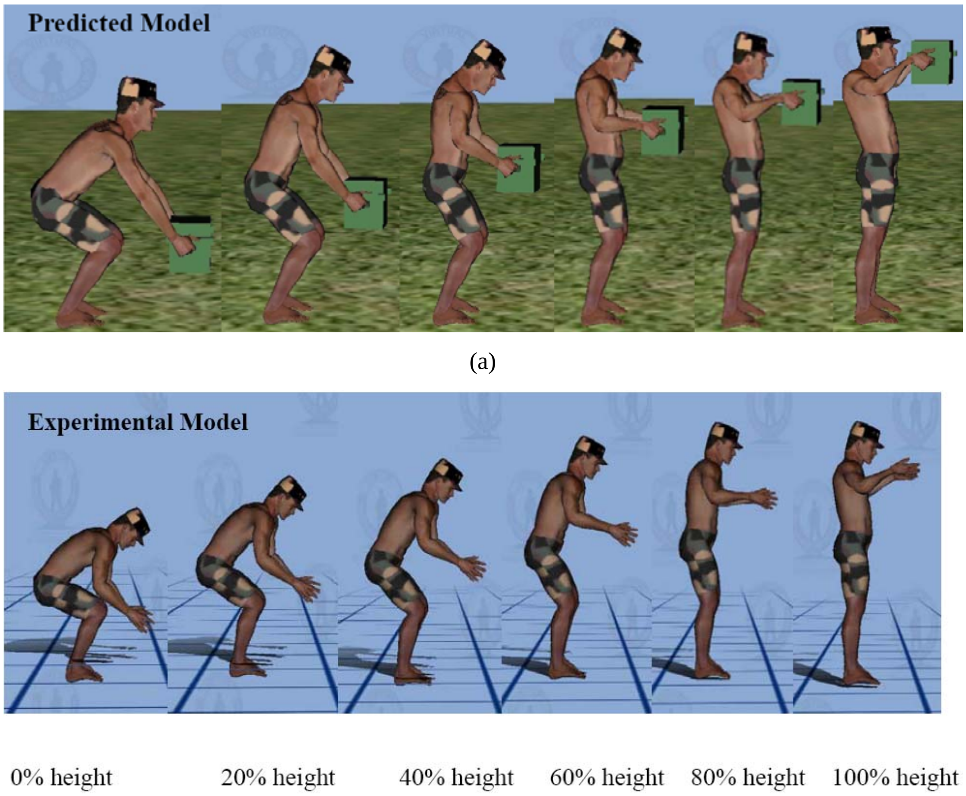


Figure 10 Selected key frames during lifting, (a) predicted model key frames (b) experimental model key frames (see online version for colours)



(b)

5 Discussion

A framework to validate the motion of predictive computer human models is presented in this work. The framework was applied, as an example, to a predictive computer human model with 55 DOF performing a box-lifting task. The framework is based on four benchmark tests comprising two qualitative and two quantitative benchmark tests. The results for the first qualitative benchmark test (which demonstrates subjective comparisons by observing videos of the simulated and experimental models) have shown a reasonable correlation between the experimental and the predictive models with an (r) value of 0.692729.

The subjective evaluation may not give information that is as accurate or specific as that obtained by the objective evaluation, but it can give some expectations to the modeller that the objective measure cannot provide. For example, the subjective measure can present how realistically the whole-body is moving during the task. It also presents images that may help in finding or localising unnatural behaviours at certain joints that could be hard to observe by just looking to the data coming from the objective evaluation. The authors found that the subjective assessment was very useful for the modeller, especially when the motion is far from natural, or the strategy of the task is different from what the model predicts. While the subjective assessment gives general information, it can still point out specific problems that can inform the quantitative assessment. For example, major differences in the whole-body motion will make the modeller think about a different objective function. Or a major problem at a joint will make the modeller add, delete, or relax some constraints at these joints.

As shown in Figure 4, some participants gave low scores to the experimentally driven avatar. One reason behind this poor evaluation is related to the difficulties associated with the level of visual perceptions and deception of the virtual world to the observer eyes. Another reason behind this rating could be attributed to the way the avatar looks. As can be seen in Figure 10, the avatars used for the animation have very detailed realistic skin and human-like features. These features may distract the attention of the observers and cause them to unintentionally check other irrelevant avatar attributes. For example, the participants were asked to focus on and evaluate the lifting determinants, but some participants commented on the way the avatar's head was moving. In general, the first benchmark test provided significant information about the acceptance of the model; however, it elucidates limited information regarding the accuracy of the determinants. This is because the model has a large DOF with strong coupling between the determinants, which makes it very hard for normal eyes to differentiate between the predicted and experimental determinants.

The results of the second qualitative benchmark test have shown some similarity between the shapes of the predicted and human TD as shown in Figure 5 and Figure 6. However, the model showed poor performance in following the shape of the ankle and shoulder flexions during the lifting cycle. The predicted model showed some potential for capturing the coupling between the TD as shown in Figure 5(b), with some poor performance in capturing the coupling between the shoulder and the ankle. The importance of this benchmark test is to detect major discrepancies, if there are any. Additionally, this test can identify any abnormal characteristics in the shape of the determinants' time history during the lifting cycle.

In terms of the quantitative comparison in the third benchmark test, the predicted lifting motion showed a reasonable correlation with the experimental data (Figure 8), where all determinants, except the shoulder flexion-extension and the ankle flexion angles, stayed inside the interval of confidence at all times and, notably, followed the mean of the subjects. The shoulder flexion-extension angle showed acceptable correlation during the first half of the lifting cycle, but poorly represents human characteristics during the second half of the motion cycle (Figure 8). One main issue in these discrepancies could be related to the model accuracy, where the experimental data was collected from real human with muscles and skin movement, while the model is based on a rigid-body dynamics assumption. The discrepancies may also be due in part to the absence of the necessary constraints on the complex shoulder motion in the model and in part to the difficulties associated with computing accurate shoulder joints from the experimental data. The discrepancies could be attributed to other parameters such as the complex interaction of the shoulder-clavicle complex motion and the motion of the wrists when the box is extended above chest level while maintaining the feet touching the floor. The ankle flexion showed similar behaviours to those of the shoulder flexion.

Unlike other human motion tasks that require a single common strategy, such as walking, the box-lifting task can be conducted using different strategies; therefore, the whole motion looks natural but the determinants' shapes could be affected by the coupling and the speed associated with the strategy being used. As can be seen from Figure 7, the model inadequately captured the early stages in the lifting process, which could involve different speeds and different lifting strategies; still, the model succeeded in capturing the following steady-state phase for both legs. It should be noted here that the ground reaction forces for box lifting were based on one subject and may be not sufficient to be used for the model kinetics validation due to the uncertainty in the lifting strategy and the possibility of the subjects leaning laterally. Therefore, the reaction forces at the hands should also be measured and used in the comparison. However, in this work we considered symmetrical lifting and assumed equal distribution of the forces on the hands and the legs.

For the key-frame in the fourth and last quantitative benchmark test, Figure 9 demonstrates the correlation between the experimental and simulated determinants with R^2 extended from 0.72 to 0.98 for most determinants with the exception of the shoulder flexion. As mentioned earlier, the shoulder performed adequately during the first half of the lifting cycle (Figure 8); however, the coupling between the shoulder-clavicle motion, the stretching in the trunk, the twisting in the wrists, and the additional motion from the lower extremity may have affected the results shown in Figure 8. For these reasons, the graph for the shoulder extension, shown in dashed lines in Figure 9, has been divided into two segments representing the first and second halves of the lifting cycle. Interestingly, in the first qualitative benchmark test, most subjects did not observe any abnormality in the shoulder motion because it is too local.

The determinant's velocity for the predicted model showed similar characteristics to those of the subject population, except for the shoulder and ankle. The predicted model could not capture the higher-frequency components, represented by the local fluctuation in the velocity. Normally, natural human motion is relatively smooth and the local fluctuations, shown in Figure 5(a), are anomalies that may represent some type of numerical noise as a result of the finite differences calculation, or because of the local movement of the reflective markers due to skin motion (Lucchetti et al., 1998; Garling et al., 2007; Anderson et al., 2010). To circumvent this problem and for the sake of the velocity and acceleration calculations, the displacement curves were curve-fitted using B-spline functions. What has been shown and applied to velocity seems to be applicable to the acceleration, as shown in Figure 6(b).

The proposed validation framework showed that the predictive lifting model considered in this work can predict to a certain level human motion during box lifting, but the model still needs additional work to capture the characteristics of the natural human motion. The proposed method was able to localise the problems in the model and showed that the model has difficulties in capturing some aspects of the task dynamics like the initial ground reaction force profile as well as some of the task kinematics like the ankle and shoulder flexion profiles. The results from this validation framework were used to locate specific abnormal characteristics in the motion determinants and to provide feedback to the developers for further refinement of the predicted lifting task.

One major contribution to the proposed validation framework is in its feedback to the modeller. For example, where there is a major difference between the predicted and human motion, the modellers will think to revise their formulation and try different objective functions in their optimisation schemes. If unrealistic motion is occurring at a certain joint, the modeller may realise that they are missing an important physical constraints, or they need to relax or tight the constraints. Because humans used different strategies when conducting their tasks, the proposed method will help the modeller to capture that. For example, for the current box-lifting task the subjective evaluation showed that the whole-body motion of the predicted model [Figure 10(a)] looks different than the whole-body motion of the experimental model [Figure 10(b)] for the key frames 0% height, 20% height, and 40% height. In this case, the objective evaluation (Figure 8) may not have the capacity or the information to capture that, because the discrepancies in the motion may show in parts of some of the determinants. The latter is very clear in the hip flexion, knee flexion, torso flexion, and shoulder flexion of Figure 8, as these determinants were outside the interval of confidence for the first 40% of the cycle. This is a good example for showing the significance of having the objective and subjective evaluations in the proposed framework. In this article, the proposed validation framework was applied to a generic predictive lifting model; however, the method is general and can be applied to any predicted model to validate its kinematics and kinetics.

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