Automated Grasp Modeling in the Human Motion Simulation Framework

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Abstract

Rapid simulation of object grasp is an important component of ergonomic analysis with digital human figure models. A large number of research papers have been presented on grasp simulation, but grasp simulation in commercial ergonomics tools has changed little in the past 10 years, in part because most research approaches to grasp simulation are difficult to implement for general-purpose simulation. This paper presents the development of a data-based, kinematic grasp simulation method that is integrated into a whole-body motion simulation framework. The right-hand motions of six subjects were recorded using a CyberGlove as they reached toward and grasped seven generic objects using five grasp types. A principal component analysis of 22 joint angle trajectories defining the hand pose motion was conducted. A regression model was developed to predict the hand motion for each of the grasp types using the object dimension scaled by hand length. The resulting model is integrated into the Human Motion Simulation Framework, which includes hand trajectory prediction and uses collision detection to fine-tune the grasp execution and terminal posture. The integration includes several novel elements, including an automatically positioned virtual end-effector and user configurability of key grasp attributes while preserving the smooth motion generation provided by the data-based model. An automotive case study using the new model demonstrated a significant reduction in the time required to produce a visually reasonable simulation.

Keywords: Grasp Modeling, Motion Simulation

1. Introduction

Ergonomic analyses with digital human models usually involve simulations of workers or product users interacting with objects with their hands. For analyses of industrial tasks, users of digital human modeling software typically spend a significant amount of time creating realistic grasps. Considerable research has been directed at creating grasp simulations, with the technology varying with the intended application.

Current kinematic models provide some functionality for simulating grasps for ergonomic application. In the kinematic models, the hand is approximated as a series of segments connected by revolute joints. The lengths of the segments are scaled as functions of the anthropometry measurements such as the hand length and breadth (Buchholz et al., 1992) based on experimental data to account for various hand sizes (Garrett, 1971). Finger joint angles are predicted given inputs of object size and hand size using various algorithms, such as regression-based geometrical contact (Buchholz & Armstrong, 1992; Choi & Armstrong, 2006) and optimizing hand-object fit (Lee & Zhang, 2005). Finger motions during reach-to-grasp have been predicted using polynomial fitting of experimental data for individual joints (Bae & Armstrong, 2011). These models, however, simulate only power grip or precision pinch for cylindrical objects. Only the hand geometry is represented, and the coordinated movement of the hand with the rest of the upper limb is not simulated.

Empirical studies have found that finger postures involve synergies, i.e., finger joint angles do not vary independently. Santello et al. (Santello et al., 1998) demonstrated that finger postures of shaping for a variety of object shapes, when analyzed using principal component analysis, exhibit significant clustering in the degree-of-freedom (DOF) space. The joint coupling may be due to the mechanical coupling produced by the tendons and tissues (Lang & Schieber, 2004; Malerich et al., 1987; von

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Schroeder et al., 1990) or simplified neuromotor control strategy.

Based on these findings, Ciocarlie et al. (2007) proposed a grasp simulation model for computer animation. The model optimized the hand-object contact by searching in the principal component space instead of the complete finger DOF space, therefore increasing efficiency and realism. However, their model did not consider geometric factors, such as hand size, that are important for ergonomic analysis. In addition, the optimization criteria was hypothesized and not validated by data.

Most approaches to grasp modeling using digital human figure models have approached the topic by integrating some features of the kinematic models and computer animation approach for ergonomic analysis. Endo and colleagues (2006, 2009) have described aspects of the development and application of a detailed hand model in the Dhaiba human model. This model incorporates detailed hand anthropometry and surface skin geometry. Recent efforts by the group have included detailed physics-based modeling of the interaction between the hand and grasp object. Biomechanical approaches to grasp prediction using detailed hand models have been presented (e.g., Lee and Zhang 2005). On the hand kinematics side, recent work by Verriest (2009), which includes simultaneous prediction of upper limb and hand pose motion, is most similar to the current effort.

In spite of the large number of research papers in this area, commercial ergonomic tools, such as Jack (from Siemens), Delmia (from Dassault Systemes), and Ramsis (from Human Solutions) provide relatively simple methods to simulate hand postures and grasp motions. All include the capability for the user to specify a grasp posture by manual manipulation of individual hand joints. All also include hand posture libraries, from which a user may select a posture similar to the desired posture, greatly simplifying the grasp posture creation process. All are also capable of posture interpolation, i.e., moving from a relaxed hand posture into a terminal posture to simulate a grasp. Each of the systems also includes some additional unique features. The Jack software includes a collision-based grasp posturing capability, which closes the hand toward a target grasp, stopping the fingers when contact is made with the target object. Jack's Task Simulation Builder allows grasp tasks to be specified through targeting using handprints, with the option to vary the number of orientation degrees of freedom that are respected at the end point.

The lack of more sophisticated grasp models in the widely used commercial ergonomics models results from, among other factors, the fact that most research is conducted using dedicated, special purpose hand models, and often requires calculation methods (for example, finite-element solvers) that are not widely available in ergonomics tools. The computational complexity of many of the models also hinders implementation.

The Human Motion Simulation (Humosim) Framework is a suite of algorithms for posture and motion prediction with digital human figure models (Reed et al. 2006). The Framework serves as a testbed for research in the Humosim Laboratory at the University of Michigan. Framework algorithms are designed so that they can be readily implemented in any human figure model, and Humosim implementations are underway in the Jack and Delmia human modeling systems. The features of the grasp model presented in this paper have been chosen to ensure that it can be readily implemented in commercial software.

The reference implementation of the Framework is developed in Jack using the JackScript interface based on the Python language. The Framework uses only the graphics environment, forward kinematics, and figure introspection (e.g., location of objects) from the Jack software, ensuring that the algorithms can be implemented in any other human model with these basic capabilities. The Framework has been used to simulate a wide range of tasks of interest for ergonomic analysis and industrial simulation, including walking and transition stepping (Reed and Wagner 2007), standing object transfers (Zhou and Reed 2009), vehicle ingress and egress (Reed and Huang 2009), climbing stairs and ramps (Reed 2009), and exerting force (Hoffman et al. 2008).

Prior to the addition of the new model, the Humosim Framework provided two grasp simulation methods. For most reach-to-grasp simulations, the Framework moves the hand and alters its pose (joint posture) to match a hand target glyph in the scene that includes a predetermined hand pose. In the absence of a hand target, a collision-based grasp model flexed or extended the joints of the hands to obtain contact with the surface of a grasp object. Heuristic weights were used to determine relative joint velocities.

This paper presents the laboratory methods used to develop the new grasp model, followed by a description of the implementation of the model in the Humosim Framework. A range of examples of the grasp motions and terminal postures is presented, followed by a brief case study using the new model for simulation of an auto assembly task.

2. Methods

2.1. CyberGlove Calibration

The hand postures (finger and thumb kinematics) of the right hand were measured using the CyberGlove (Virtual Technologies, Palo Alto, CA) shown in

Figure 1. Each glove has 22 sensors recording finger and thumb postures. The nominal sensor resolution is 0.5°.

Figure 1. CyberGlove. Sensors are located in stitched channels visible on the back surface of the glove.

A calibration procedure was carried for each subject similar to those used in other studies using the CyberGlove (Rezzoug and Gorce, 1999; Rezzoug and Gorce, 2008; Santello et al., 1998). Subjects were asked to put their right hand with glove on flat on the table, fingers together, while the MCP, PIP, and DIP joint angles were recorded. These joint angles were defined as 0° as the fingers were straight. Secondly, subjects were asked to bend each joint while fitting the dorsal sides of joints to wood blocks cut to specific angles. The angles for MCP joints are -25°, 45°, and 90° (for thumb MCP joint are 0°, 45°, and 75°). The angles for PIP joints are 45° and 90°. The angles for DIP joints are 45°, and 75° (for thumb IP joint are 0° and 45°). Flexion was assigned positive. The sequence of angles was randomized. Each angle was replicated two times for each joint. A calibration relationship was obtained using linear regression on the resulting data. The abduction angles between fingers were calibrated using the method proposed by Kessler *et al.* (1995), where subjects put neighboring fingers in contact with nails sticking out of a board such that the spread of two fingers was at a particular angle. The abduction angles were 0°, 15°, and 30°.

The thumb CMC joint sensors of the CyberGlove were calibrated using a new method modified from the work by Griffin *et al.* (2000). We created a hand kinematic model with three DOFs for the thumb CMC joint, while the CyberGlove provides two sensors (thumb roll and thumb-index abduction sensors) for recording CMC movement. The following linear relationship was assumed:

$$\begin{bmatrix} \theta_{abd} \\ \theta_{flex} \\ \theta_{rot} \end{bmatrix} = \begin{bmatrix} A_1 & A_2 \\ A_3 & A_4 \\ A_5 & A_6 \end{bmatrix} \begin{bmatrix} V_{troll} \\ V_{tiabd} \end{bmatrix} + \begin{bmatrix} B_{abd} \\ B_{flex} \\ B_{rot} \end{bmatrix} \quad [1]$$

The coefficients in the A matrix were estimated using a closed-loop method. Griffin *et al.* (2000) proposed a method in which subject moves thumb while maintaining the rolling contact between the thumb tip and index finger tip together. The coefficients are then obtained by minimizing the separation of the finger tips over the set of data points using a least squares fit. However, we found that this movement could not cover the typical range of motion (ROM) of the CMC joint. As a result, the estimated coefficients could not well capture the CMC kinematics in task motions. Therefore, we asked subject to perform four movements in which subject touches the thumb tip sequentially to the 1) index finger tip, 2) palmar side of the PIP joint of the index finger, 3) middle finger tip, and 4) palmar side of the PIP joint of the middle finger. This procedure increases the range of CMC movement during calibration, providing improved estimation of the coefficients.

2.2. Laboratory Study

To develop the grasp model, a laboratory study was conducted in which subject was asked to reach for and grasp objects with different shapes and sizes. The dependent variable was finger movements measured by CyberGlove. The independent variables were object shape, size, and grip type. Table 1 lists the objects used as the targets. The grip types were power grip, precision pinch, thumb-index fingertip pinch, chuck pinch, and lateral pinch. For the cylindrical objects, only power grip and precision pinch were tested. For the rectangular cubes, all grip types were tested except for power grip.

Table 1. Target objects

Object shape	Object size	Grip type
Cylinder	25.5 cm in length 1.5 cm in diameter	Power grip; Precision pinch
Cylinder	25.5 cm in length 7 cm in diameter	
Cylinder	25.5 cm in length 10 cm in diameter	
Rectangular cube	6 x 6 x 1.5 cm	Thumb-index finger tip pinch; Chuck pinch; Precision pinch; Lateral pinch
Rectangular cube	6 x 6 x 3.5 cm	
Rectangular cube	6 x 6 x 6 cm	

Subjects sat in front of a table. The height of the table was adjusted to the elbow height for each subject. The subject's right hand was initially rested in a relaxed posture with palm down on the table with elbow angle approximately 90 degrees. The right arm was aligned with the object. For cylindrical objects, they were vertically fixed in front of the resting right hand with a distance of 20

cm. Rectangular cubes were located on a fixture such that the side of varying length was vertical, with a distance of 20 cm horizontally to the resting right hand, and approximately 15 cm above the table (Figure 2).

In each trial, subjects were asked to reach for and grasp the object with the right hand at their natural speed. Trials were blocked for each object, with the object order randomly selected for each subject. The sequence of grip types was randomized within each block. Each trial was 3 seconds. Practice trials were conducted for each object and grip type combination. Each condition was replicated twice.

Six university students (4 males and 2 females, age between 20 and 26 years, mean age 22.7 ± 2.8) were recruited for the experiment. All participants were right-handed and were free of any movement disorders. They gave written informed consent in accordance with our University IRB regulations. The average hand length was 19.1 ± 0.6 cm for males and 17.1 ± 1.6 cm for females. The hand lengths ranged from 8th percentile to 49th percentile for males, and from 1st percentile to 59th percentile for females based on the population data from Garrett (1971).

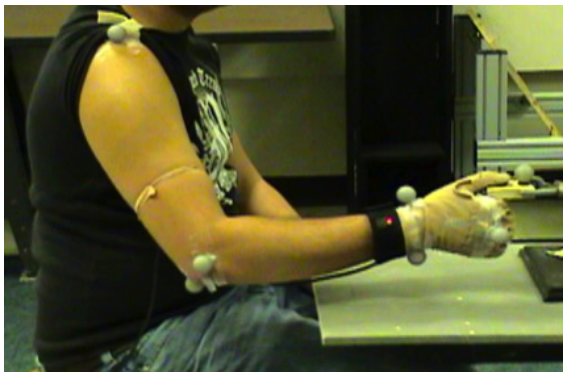

Figure 2. Example trial of grasping a rectangular cube (6 x 6 x 1.5 cm) with a lateral pinch.

2.3. Statistical Analysis

Separate analyses were conducted for each grasp type (four pinches and power grip). The joint angle trajectories were normalized to unit time for analysis (Figure 3). The primary period of motion was extracted by identifying (1) the first point at which at least one joint angle moved at a speed greater than 1.5 deg/s and (2) the point at which all angles were moving at less than 1.5 deg/s. The motion duration was defined between these landmarks, and the data were resampled using linear interpolation to a uniformly spaced 60 samples. Each grasp motion was represented by a matrix having 60 rows (normalized time steps) and 20 columns (joint angles).

A principal component analysis was conducted on the motion data after flattening each motion matrix to 200-element vector. The first 20 principal components (PCs), which accounted for 97 percent of the variance, were retained for modeling (Figure 4).

Within each grasp category, a regression analysis was conducted to predict the PC scores as a function of effective aperture, defined as the object breadth (for pinch objects) or cylinder diameter (power grip) divided by hand length. A separate analysis of grasp motion duration found no influence of grasp type or aperture. The mean grasp motion duration of 0.95 seconds was used for subsequent prediction, except that the motion is accelerated for short reach-to-grasp movements.

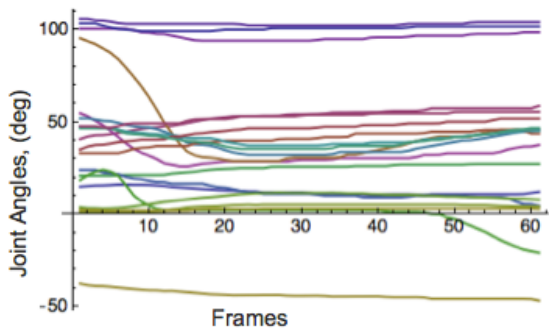

Figure 3. Sample joint angle trajectories for one grasp motion normalized to 60 frames.

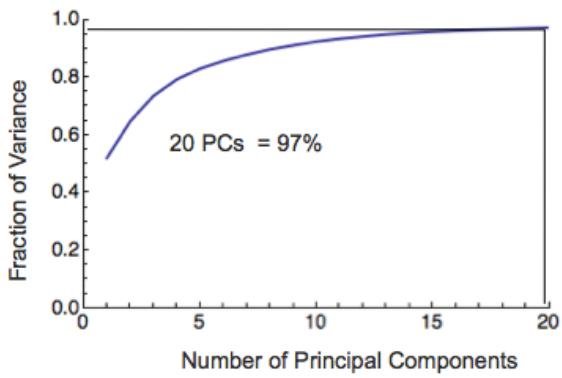

Figure 4. Fraction of variance with number of principal components retained.

2.4. Hand Location and the Virtual End Effector

The Framework plans hand trajectories by computing the path of a particular point on the hand, termed the end effector by analogy to a robotic end effector (Reed et al. 2006). Prior to the current development, the Framework always used the base of the palm segment (located at the wrist joint) as the end effector, and predicted both the

translation and rotational components of the trajectory to attain a particular hand position and orientation. This approach has been very effective when the terminal hand position and orientation was specified by the user or could be easily inferred from the task requirements. However, hand tasks are rarely performed using the wrist as the point of action; much more commonly the fingers or palm are the effective points of contact with the object. For example, in a movement to press a button with the tip of the index finger, the end effector should be considered to be located at the fingertip.

As part of the current work, a new, locatable end-effector was introduced. The user can specify the location of the end effector on the hand (for example, at the center of the palm) or on another object attached to the hand, such as at the end of a drill bit. This functionality allows reaches to be planned to place the end effector at target locations while preserving the smooth characteristics of Framework reaches.

The locatable end effector also allows simulation of reduced degree-of-freedom targets. In many task scenarios, a variety of hand or tool orientations are feasible within task constraints. For example, a nut runner can be used in a large number of possible positions, provided that the tip be located at the appropriate position (three degrees of freedom) and the axis of the driver be aligned with the fastener (two degrees of freedom). The Framework provides user configurability for six degrees of freedom (the default), five degrees of freedom (pivoting around one axis) and three degrees of freedom (translation only).

The addition of this functionality increases the complexity of the inverse kinematics calculations that are used to posture the upper limb. The redundancy is resolved by minimizing wrist deviation, based on the observation that workers will tend to use near-neutral wrist postures when the task permits. This approach to wrist DOF is similar to that used by Verriest (2009).

For automated grasp simulation, the end effector is relocated by the software based on the characteristics of the object to be grasped. The end effector is "virtual" because it not necessarily located on any part of the hand geometry, but rather reflects the center of the grasp action. The concept is most easily described for two-finger pinch grasps, where the virtual end effector lies at the midpoint between the pads of the thumb and forefinger. For power grips of approximately cylindrical objects, the end effector lies along the axis of the cylinder adjacent to the palm center.

2.5. Integration with the Framework Reach Module

The new grasp module has been fully integrated with the Framework motion simulation capability. Figure 5 shows a schematic representation of the planning and execution of a reach-to-grasp motion. Such a motion can be executed as part of a larger simulation of either standing or seated tasks.

The user specifies a target to be grasped. Based on an analysis of the object bounding box, the Framework chooses a grasp type and grasp target location with respect to the object, including the number of target degrees of freedom. For example, for an object with a bounding box similar to a cube, with an overall size of approximately 25% of hand length, the Framework would choose a precision pinch with three degrees of freedom (translation only). Based on the selected grasp type, the scaled aperture target is calculated using the object dimensions relative to hand length. The PCA grasp model is then executed, computing a representative grasp motion (including terminal posture) for the specified grasp type and aperture. Based on the terminal posture, the virtual end effector target is positioned relative to the palm and the target for the end effector is located on the object. In the case of a 3-DOF pinch, the target is located at the center of the object.

The overall hand motion duration and trajectory is computed as described elsewhere (Reed et al. 2006; Faraway et al. 2007). For motion durations longer than 0.95 s, the pose motion given by the PCA model (which includes opening from neutral and closing onto the target) is executed starting 0.95 s prior to the end of the motion. For shorter-duration motions, the pose motion is accelerated to match the reach duration. As the hand approaches the target, the hand pose follows the planned grasp motion. If collisions between the fingers and object are detected, the finger motions run in reverse to open the fingers as needed. This step is critical to simulate the common situation in which the fingers skim over the surface of the object prior to grasp. The realism of this aspect of the simulation is dependent on the accuracy of the hand trajectory. If the trajectory prediction is poor, clearing finger collisions will produce unrealistic hand postures. In practice, this can often be ameliorating by specifying a larger target aperture, which produces a larger hand opening prior to grasp.

As the final hand position is reached, the collision-based grasp runs forward to close the required digits onto the object, using relative finger joint speeds based on the current joint angle trajectories. This allows realistic grasp of irregularly shaped objects with a model developed using generic objects.

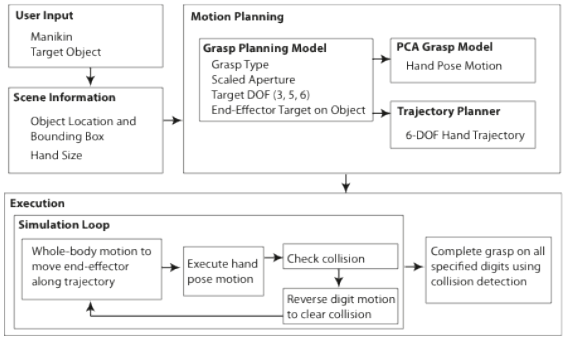

Figure 5. Schematic representation of reach-to-grasp simulation in the Humosim Framework.

In some cases, the predicted motion or grasp posture is not as desired. For example, the object to be grasped might be a tool with a particular grasp location not readily identifiable from the bounding box. The user has the opportunity to rapidly alter all of the key parameters of the reach that were predicted using by the automated algorithms, including grasp type, target location, target DOF, and aperture.

3. Results

Figure 2 shows examples of the five available grasp types on the Jack manikin hand. Figure 3 shows frames from reach-to-grasp motion simulations.

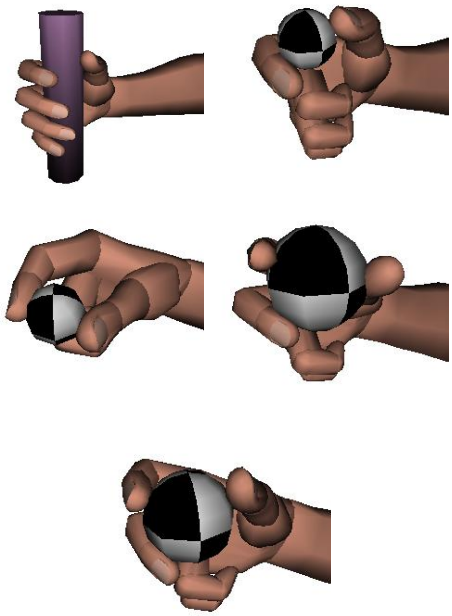

Figure 6. Grasp types (from upper left): power, lateral pinch, two-finger pinch, chuck pinch, precision pinch.

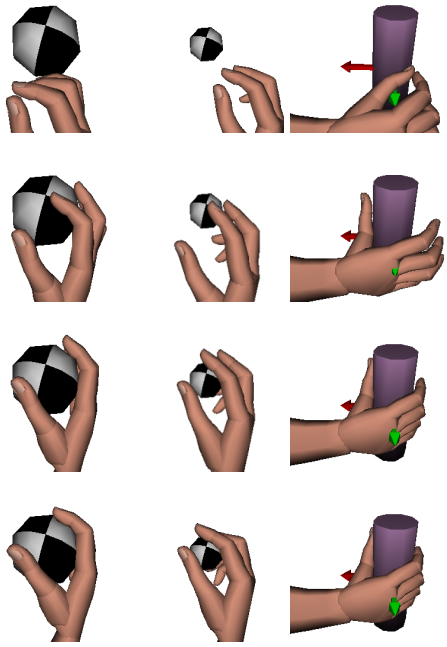

Figure 7. Frames from automatic reach-to-grasp motion simulations (top to bottom).

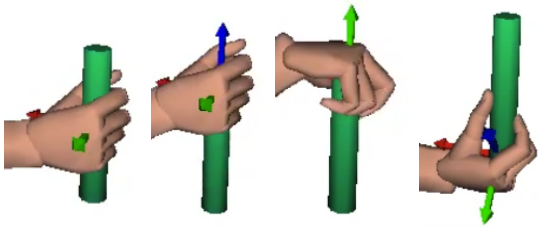

Figure 8. Illustration of alternative grasps of a cylinder produced after the user moved the grasp target (coordinate arrows) to different positions and orientations.

4. Case Study

The new grasp model was exercised in an automotive case study comparing the performance of the Siemens Classic Jack model with and without the Framework. In the simulated task, the worker reaches within a door assembly to pull a wiring harness into position. Figure 9 shows images from the case study. In addition to producing more realistic hand postures, simulation time for the case studies was reduced by 67% for one operator. Improved consistency across simulation users and reduced skill requirement is expected due to the use of predictive models.

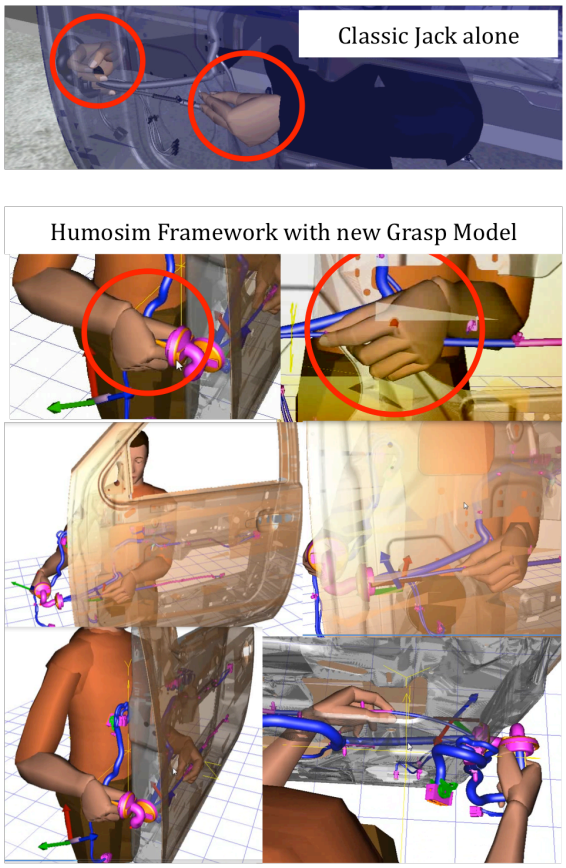

Figure 8. Illustration of case study results.

5. Discussion

The methods and model presented here are similar in several basic aspects to previous studies. PCA has been used to simplify hand posture and motion data by a number of researchers, notably Endo et al. (2009), who also examined ease of grasp in PC space. Recent data-based approaches to grasp pose simulation have been described in Beurier et al. 2007 and Verriest (2009). The current work differs from the latter primarily in the data gathering methodology (CyberGlove vs. optical motion capture), in the use of PCA to create an empirical model, regression analysis to create generalizable predictions based on a scaled aperture parameter, the use of the automatically located virtual end effector to target reaches, and in the integration of the method into a whole-body, general purpose ergonomic simulation tool.

The current integration is novel, to our knowledge, in that it combines the use of a data-based grasp model that is tuned on the fly using collision detection, flexible reach trajectory planning, and optional user override of critical variables that are otherwise set automatically. One challenge in creating usable motion simulation models is that the models must work with minimal user input while also allowing the user to intervene at a variety of levels without reverting to manual methods. In the current context, the use of the reach targeting through the virtual end effector with variable degrees of freedom provides a large amount of customization with minimal user input.

The model is limited by the relatively small number of subjects (6) and grasp types (5). The CyberGlove allows fast, accurate measurement of hand posture, but the glove may alter hand behavior. The overall performance of the model in automatic mode is limited by the difficulty in selecting the correct grasp type for a particular situation. This problem is extremely difficult to solve with high accuracy in the general case, due to the large amount of context-dependent knowledge that is required. In our judgment, it is more important for ergonomic tools to provide the software user with the ability to rapidly and accurately retarget the grasp than to have the grasp automatically generated at the correct location on the grasp object.

The current model has been developed for use in current commercial human ergonomic software systems. The constraints and typical applications of these systems have been reflected in the design choices. For example, the model is entirely kinematic and is focused on rapid generation of plausible postures for any object and hand size rather than biomechanical mechanical analysis of the grasp. However, the kinematic modeling described here could be an important component of a biomechanical grasp model. Future steps include adding grasp types, tuning the terminal posture based on grasp quality criteria, and incorporating improved prediction of hand approach vectors.

6. Conclusion

The Humosim Framework now incorporates a data-based grasp model that predicts realistic movement trajectories for 22 hand degrees of freedom. The grasp model, which is parameterized by five grasp types and a continuous grasp aperture variable, provides an automated way to obtain accurate grasp motions for simple object shapes and reasonable motions for complex shapes that have not been studied in the lab. Importantly, the new grasp model is fully integrated into the reaching and grasping capability of the Framework. Users can take advantage of the default behavior to conduct rapid simulations or can override some or all of the parameter values to achieve a large amount of customization. The model has been designed for rapid implementation in commercial modeling tools, such as Jack and Delmia. A case study using the new model to simulate an automotive assembly task demonstrated improved grasp realism with a substantial reduction in the time required to prepare the simulation.

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