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Motion/Posture Modeling and Simulation Verification of Physically Handicapped in Manufacturing System Design

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Abstract: Non-obstacle design is critical to tailor physically handicapped workers in manufacturing system. Simultaneous consideration of variability in physically disabled users, machines and environment of the manufacturing system is extremely complex and generally requires modeling of physically handicapped interaction with the system. Most current modeling either concentrates on the task results or functional disability. The integration of physical constraints with task constraints is far more complex because of functional disability and its extended influence on adjacent body parts. A framework is proposed to integrate the two constraints and thus model the specific behavior of the physical handicapped in virtual environment generated by product specifications. Within the framework a simplified model of physical disabled body is constructed, and body motion is generated based on 3 levels of constraints(effecter constraints, kinematics constraints and physical constraints). The kinematics and dynamic calculations are made and optimized based on the weighting manipulated by the kinematics constraints and dynamic constraints. With object transferring task as example, the model is validated in Jack 6.0. Modelled task motion elements except for squatting and overreaching well matched with captured motion elements. The proposed modeling method can model the complex behavior of the physically handicapped by integrating both task and physical disability constraints.

Key words: physical handicapped, motion/posture modeling, manufacturing system design

1 Introduction

Non-obstacle design is critical to tailor handicapped workers and maximize the usability of whole manufacturing system. Design for people requires quantitative consideration of all relevant aspects of human variables. Many tools have been developed to perform human behavior analysis in virtual environments, such as Jack[1], SAMMIE[2], MANERCOS[3], and SAFEWORK[4]. These tools are commonly used by designers to perform occupational ergonomic analysis on a virtual mock-up by immersing a virtual human controlled by direct or inverse kinematics in the task environment. Within the above applications, the human models account for about 90% of the population, but not the handicapped population. A new approach, called "design-for-all"[5–6] aims to perform accessibility tests on an even wider range of the population.

It is necessary to specify the characteristics of the operator, the machine, the environment and the operator's interaction with machine and environment. In the virtual environment, functional description can be used to simplify the interaction between the humanoid and the objects in simulated scenario[1]. To simulate functional ability, there are varying notions such as anthropometric data, functional ability, admissible joint angles as well as physiological data like maximum strength, recovery time and fatigue[7–10]. BADLER, et al[11], proposed a framework named PAR (Parameterized Action Representation) to simulate the interaction between human and machine in the dimension of movement. KALLMANN, et al[12], used the Smart Object framework as physical simulator to reflect the humanoid interaction with environment. SAFONOVA, et al[13], proposed a framework simulating the anthropometric characteristics in task-specific workspaces. RODRIGUEZ, et al[14], modeled and simulated fatigue associated with joint movement. The above methods provide good insights into how to simulate functional ability of the human interacting with machine, tool and environment system.

To simulate the functional ability of the physical handicapped, PORTER, et al[2], set up a database containing movements of physically disabled people. Using this data, it is possible to display problems that each recorded individual may experience. However, recorded behaviors cannot easily be applied to new tasks or individuals. REED, et al[10], reviewed a variety of approaches to find that most posture and motion prediction methods have been focused on relatively narrow range of tasks and thus introduced a new methodology, the Human Motion Simulation

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(HUMOSIM) Framework intended to be extensible to most human movements of interest for ergonomics. By HUMOSIM framework, motion and posture can be predicted based on constraints derived from end-effectors.

To simulate functional interaction of the disabled with the product system, constraints not only lies in tasks but also variances in functional disability of handicapped body part. The integration of physical constraints with task constraints is far more complex because of functional disability and its extended influence on adjacent body parts. This study presents a framework dedicated to integrate the two constraints and thus model specific behavior of the physical handicapped in virtual environment generated by product specifications. Based on 3 levels of constraints, the model can predict physical capacity in the dimension of joint kinematics and muscle dynamics associated with product use. The model can calculate the posture and motion of the physical handicapped based on the optimization of strength and torque under physical and dynamic constraints of physical disability. To validate the model itself, the study uses material handling task (squatting and reaching) as an example and compare modeled results with those from the motion capture.

2 Modeling Method

Generally speaking, human performance in task interaction can be evaluated at three main levels: task level, occupational level and physiological level[11]. This study presents a disability constrained model to evaluate all three levels of performance when human interacts with product system (Fig. 1).

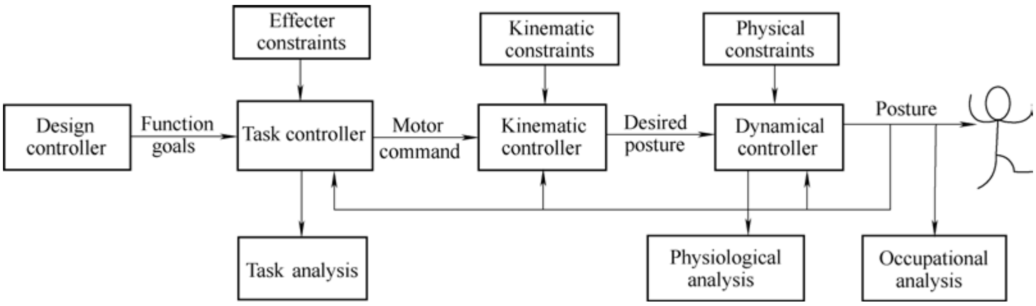


Fig. 1. Constraint-driven model of physical handicapped motion/posture

At task level, human biomechanical laws concluded by empirical studies are required. For example, Ref. [12] computes the strength maneuvering on a certain handle by input of anthropometric parameter and handle size. Occupational analysis can be conducted in simulation scenario. Physiological analysis deals with forces associated with motion, implying the information of fatigue and musculoskeletal pain. The main problem with the physiological method is modeling muscle function. However, to add physiological analysis into simulation system can help retrieve the kinetic parameters such as forces and torques, which is a critical factor evaluating the usability index of the product At occupational level, motion data collected can be connected with the individual, which makes the analysis realistic.

Constraints led to functional disability during task can be categorized as 3 groups: appearance(effectors) constraints such as broken arm or amputation, kinematics constraints, such as inaccurate pointing and less degree of freedom (DOF) of joints and physical constraints such as strength limits. Fig. 1 shows how controllers operate at three levels of constraints.

There are 4 controllers in this model. Human, product and environment variables entered into the interaction controller with the constraints result in variations of the virtual humanoid's posture until the posture is achieved. First, design controller conveys human function reflected as a set of function goals. Data flowing into the task controller are from the product specifications. For instance, holding on a hand tool can be translated as grasping the hand tool handle and the grasp can be transmitted totask controller. Task controller will be constrained by physical disability, named by effecter constraints(E). For instance, if the right hand of the user is dysfunctional and has weak grip strength, E is the disabled right hand. Then the controlled motor commands will be passed to kinematics controller. This controller is responsible for generating a posture requiring for grasping the hand tool. Kinematics constraints are passed as parameters of controller and together generate a posture. The algorithm behind this controller is function of motor command, which will be discussed in following sections. The generated posture will be controlled by dynamic controller, which can generate forces required for this posture, and produce final posture in holding on hand tool tasks. A physical simulator is enabled to generate dynamic physics like forces and torques on the humanoid to achieve desired posture. Physical constraints such as strength limits are parameters to controller. The algorithm of dynamic controller constrained by physical factors will be discussed in section 3. At last obtained posture is given back to task controller to determine whether function goal is achieved. When new changes were made to task controller, the process shall go on through the kinematics controller and dynamic controller. New postures can be generated by changed kinematics controller and dynamic controller. Three levels of constraints are the key to model motion and posture of physically handicapped during task performance and to visualize functional capacity of the physically disabled. And the outputs of physiological analysis and occupational analysis can provide ergonomic analysis on product design.

3 Motion and Posture Generation

There are two approaches currently for motion prediction: empirical statistical modeling and inverse kinematics or biomechanics. The first approach uses anthropometric data and motion patterns collected in lab that are statistically analyzed to form a predictive regression model of posture with rule-based adjustments to accommodate the infinite motions possible. The second approach uses common inverse kinematics characterization to represent mathematically feasible postures. Inverse kinematics and optimization are used to assess the objective functions, such as joint limitations, physiology cost and thus generate the optimal posture/motion. In this paper, the mixture of the two approaches is applied to the algorithm of kinematics controller and dynamic controller (Fig. 2).

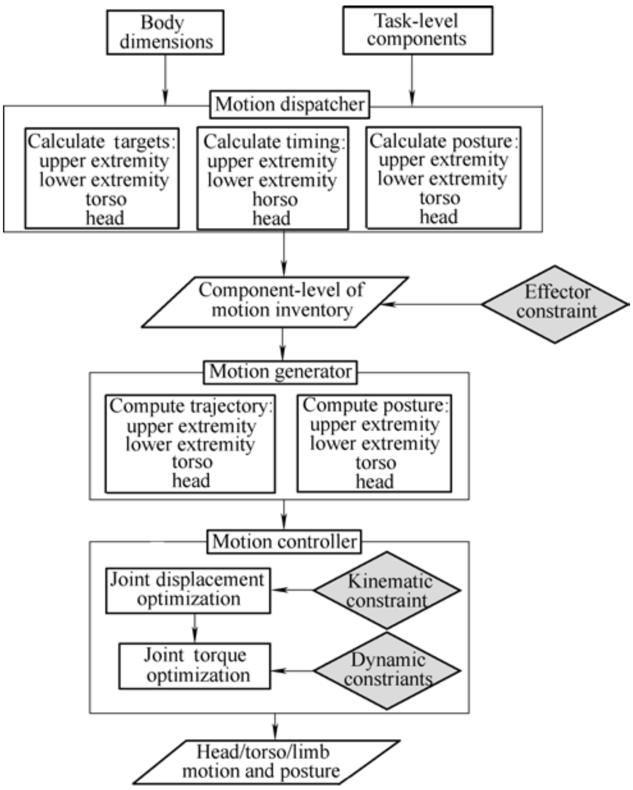


Fig. 2. Motion generation process

To generate motion/posture, motion elements are dispatched to each body component. 4 modules (gaze module, upper-extremity module, torso module and lower-extremity module) related to the body dimensions are built up to manipulate the controllers based on different DOF kinematics skeletal model.

Constrained by the task variables, kinematics variables and dynamic variables, the values are to be adjusted based on function optimization. The generation process consists of 3 main parts: (1) A set of design variables, which are joint profiles(i.e., joint angles as a function of time) and the torque profiles at each of joint; (2) Multiple cost functions to be optimized, which are human performance measures that represent functions that are important to accomplishing the motion(e.g., energy, speed, joint torque); (3) Constraints on the motion(e.g., collision avoidance, joint ranges of motion, strength limits). Motion accomplishment requires optimization of multiple cost functions such as energy, speed and joint torque. The optimization is under the constraints such as ranges of motion and force requirement. In this paper, both joint angle and torque values are generated by optimizing cost function in kinematics and dynamic dimensions.

3.1 Kinematics skeletal model

Hanavan's fifteen finite segment model of the human body is applied to represent a simplified model of physical handicapped body (Fig. 3)[13]. This model consists of upper arm, forearm, hand, torso, upper leg, lower leg, foot and head. 15 segment links are the maximum and number of the links is deducted based on the availability of body parts. For a right under-knee prosthesis wear, the human body can be described by 14 finite segment model, combining right lower leg and right foot as one finite segment.

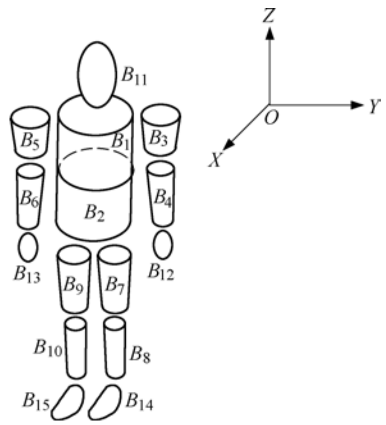


Fig. 3. Human body of 15 segment links

DOF of each link representing the fidelity of human modeling. Determining an appropriate level of fidelity is critical. Not every DOF for the human body is considered, especially with respect to the spine and neck. For example, a complete spine(24 vertebrae with 72-DOF) may not be necessary when we consider how spine affects the overall motion of the body. The method defines degrees of freedom by specific components in difference scenarios. In lifting task scenario, an upper-extremity segment of torso-spine-shoulder-arm is built on 15-DOF while in reaching task scenario the same body segment is built on 14-DOF without considering the one DOF of torso[14].

3.2 Joint kinematics optimization

Various human performance measures provide objective functions of optimization formulation. The most popular function is concerned about joint displacement, energy, and effort. Factored by the kinematics constraints, the optimization is firstly based on joint displacement, which is given as follows.

Joint displacement profile is expressed as

$$F(q)=\sum_{i=1}^{n} w_i(q_i-q_i^{\mathrm{N}}),\quad q_i^{\mathrm{L}}\leqslant q_i\leqslant q_i^{\mathrm{U}},\tag{1}$$

where q_i^{N} is neutral position of joint i, and selected as a relatively comfortable posture, a standing position with arms at each side. w_i is deviation caused by kinematics constraints of joint i and can be determined later by feed-forward network training based on motion capture data of subjects. $q_i^{\mathrm{L}}, q_i^{\mathrm{U}}$ represent upper and lower limits of ith joint angle, derived from physical constraints of human motion. They are measured by medical tests or defined by the occupational test inventory of specific tasks.

As stated above, the end-effectors' vector can be defined by specific task variables. The inverse kinematics is used to calculate q. For the serial chain and tree-structured system, the joint velocity vector within the operation space can be described as

$$\varepsilon=J(q_i)\dot{q}_i,\tag{2}$$

where ε is the m dimension of position vector of end-effecter and is defined by design controller and task controller. $J(q_i)\in \boldsymbol{T}_{m\times n}$, $\boldsymbol{T}_{m\times n}$ is the $m\times n$ Jacobian matrix of velocity vector, m is the dimension of end-effecter and n is DOF of joint i. $\boldsymbol{T}_{m\times n}$ can be obtained by partially differentiating to the joint speed through Eq. (3):

$$\dot{q}_n^0=R_n^0\dot{q}_n=R_1^0R_2^1\cdots R_{i-1}^i\cdots R_n^{n-1}\dot{q}_n, i=1,2,\cdots,n.\tag{3}$$

The Denavit and Hartenberg representation method (DH method) was used to sketch coordination system of each segment link. The DH method is based on characterizing configuration of joint i with respect to joint $i-1$ by a 4×4 homogeneous transformation matrix representing each joint's coordinate system as shown by Eq. (4):

$$R_{i-1}^i=\begin{pmatrix}\cos\theta & -\cos\alpha\sin\theta & \sin\alpha\sin\theta & a\cos\theta\\ \sin\theta & \cos\alpha\sin\theta & -\sin\alpha\cos\theta & a\sin\theta\\ 0 & \sin\alpha & \cos\alpha & d\\ 0 & 0 & 0 & 1\end{pmatrix},\tag{4}$$

where α, θ, d and a denote the values indicated in Fig. 4.

q and $\ddot{q}$ can be obtained separately by integration and deviation to $\dot{q}$,

$$\dot{q}_i=J^{+}(q_i)\varepsilon,\tag{5}$$

$$\ddot{q}_i=J^{+}(q_i)[\dot{\varepsilon}-\dot{J}(q_i)\dot{q}_i],\tag{6}$$

where $J^{+}(q_i)$ is the pseudo inverse of $J(q_i)$.

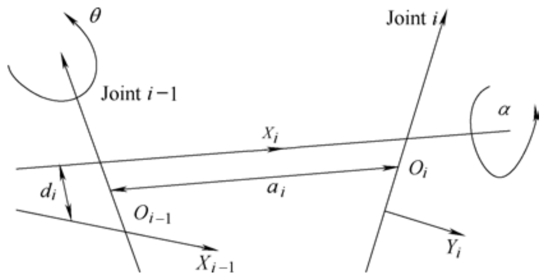


Fig. 4. Relation between two coordination systems with four parameters (α, θ, d and a)

3.3 Joint dynamic optimization

Energy is drive force of joint displacement while effort is a substitute to changing posture from one point to another. Further optimization formulation is conducted to compute the factor of dynamic constraint for multi-DOF body segments.

Joint displacement profile can be expressed as

$$F(q')=\sum\nolimits_{i=1}^{n} w'(q_i'-q_i)^2.\tag{7}$$

$$\begin{cases}\min F(\tau)=\sum\limits_{i=1}^{n} w_i'|\tau_i|,\\ \text{s.t.}\, F(q_i')\in F(q_i),\\ \qquad \tau^{\mathrm{L}}\leqslant\tau_i\leqslant\tau_i^{\mathrm{U}}.\end{cases}\tag{8}$$

w_i' is deviation caused by physical constraints. τ_i is calculated through Eq. (9) according to Ref. [15]:

$$\tau_i=M_{ik}(q_i)\ddot{q}_i+\sum J^{+}(q_i)m_{ik}g+\sum J^{+}(q_k)F_k,\quad i=1,2,\cdots,n.\tag{9}$$

m_{ik} is the mass of link (i, k), F_k is the external force on the joint k . Joint i and k are the two joints on each side of the link (i, k). $M_{ik}(q)$ is the mass inertia of link (i, k) and can be calculated by Eq. (10):

$$M_{ik}(q)=\sum\nolimits_{j=\max(i,k)}^{n} R_j\left\{\frac{\partial T_j(q)}{\partial q_k}I_{ik}\left[\frac{\partial T_j(q)}{\partial q_i}\right]^{\mathrm{T}}\right\},\quad i,j,k=1,2,\cdots,n.\tag{10}$$

where I_{ik} is the mass inertia of link (i, k), $I_{ik}=m_{ik}l^2/3$.

4 Lifting Task Modeling and Method Validation

To validate the calculation model, the paper sets up an experiment of reaching and lifting task. Five under-knee prosthesis wearers on the right sides with varying body dimensions, age, and strength participated in the study. The task is bending the torso, reaching for a target in front of the subjects on the ground and lifting it up to overhead level (45°). Mass of the object is 2 kg. In the Siemens Jack 6.0 human modeling was made based on the motion captured by VICON system(Qualysis MacReflex) with six cameras at 50 Hz. Twenty-one markers were attached to the subjects at predefined body landmarks. The landmarks were used to estimate joint center locations using custom software(VICON BodyBuilder). And matching human modeling is made by defining the joint angle and displacement calculated based on the proposed model and realized in Jack environment as well (Fig. 5).

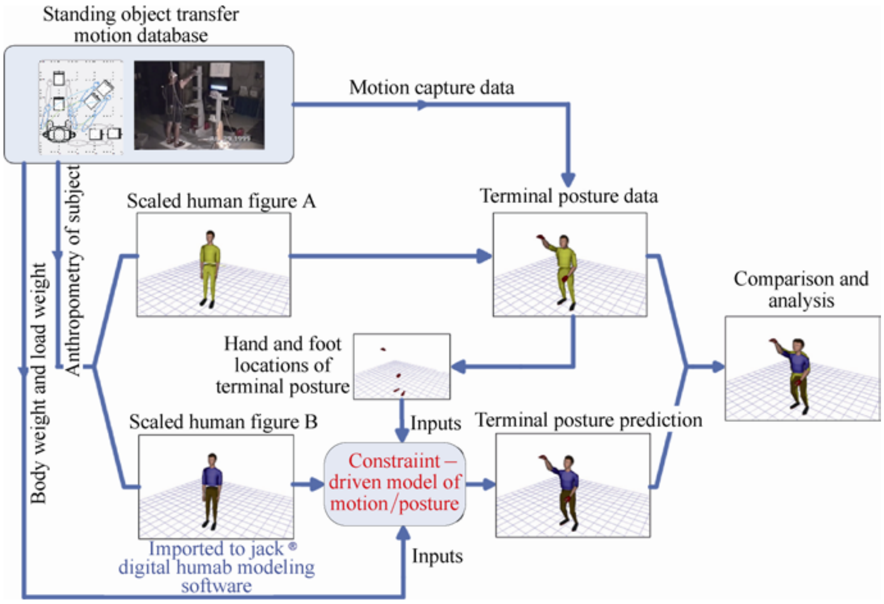


Fig. 5. Schematic diagram of posture validation

Feed-forward neural network was built up to calculate relative importance of each joint w_i and w_i'. The example extracted values of w_i and w_i' from recorded movement. The skeleton used to reproduce arm motions has 12 joints (neck, L/R wrist, L/R elbow, L/R shoulder and a virtual joint on the spine, L/R hip and L/R knee). Each of 12 joints has different DOF. For each DOF of every joint, a weight is computed in the dimension of time. In lifting and reaching task scenario, there are 20 weight groups for all joints. Jointplacement and joint moment calculated from motion capture data are used as input to train the neural network to get satisfactory weights. The learned weights of 2-DOF knee joint (healthy side) of bending as part of the whole task are shown in Fig. 6. Value ranges of each joint on different DOFs are measured by experiment conductors. In practice, they can also be defined by medical and occupational tests.

Task simulation of subject 5 is used to validate the model. The anthropometric data of subject 5 (Table 1) is input of the optimization model. Subject 5 wears prosthesis on the right side. Where the mass is calculated based on the length of each link across the same mass density except for the disabled side of leg.

Manipulated by weights at each corresponding time point, the model calculated the optimization angles of 12 joints. Results are put into Jack environment and a manikin is created and compared to another manikin created by motion capture data. The prosthesis foot (right) is marked with black and white. Fig. 7 shows samples frames of the results, where the person with yellow shirts represents the observed posture by motion data capture while blue shirt stands for the posture predicted by the model.

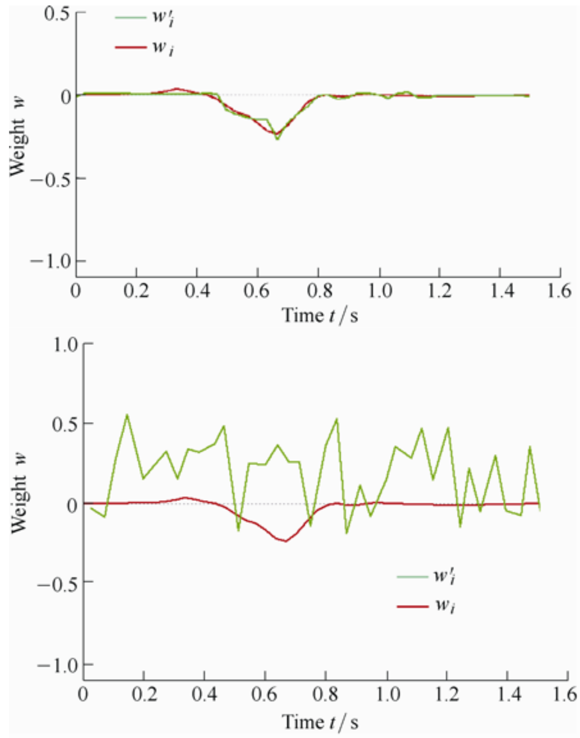


Fig. 6. Weights of the knee's 2-DOF during the bending task

In Fig. 7, yellow shirt is almost overlapped with blue shirt. The most obvious mismatching lies in two extreme postures: squatting and bending to the lowest and reaching overhead. Thus, further calculations are made on the two extreme postures of all five subjects. Fig. 8 shows similar mismatch can also be observed on other 4 subjects. There might be at least two reasons to explain the variance. Firstly, weights obtained from neural network training are based on small number of subjects, which decreases model prediction reliability. More subjects are required to train weight neural network and thus diminish the variance across different subjects. Secondly, physical disability causes bigger variance in task modeling when the disabled body parts exert great effort to implement the task. Bending to the lowest and overhead reaching requires great efforts, causing whole body instability.

Table 1. Anthropometric data and mass properties of subject 5

Part	Length l/m	Mass m/kg	Moment $M/(\mathrm{kg \cdot m^2})$
Hand	0.214	0.55	0.001
Forearm	0.402	2.02	0.012
Upper arm	0.405	1.46	0.011
Torso	0.712	28.88	0.294
Upper leg	0.387	10.32	0.172
Sound leg part	0.421	10.64	0.184
Amputee	0.386	3.92	0.210

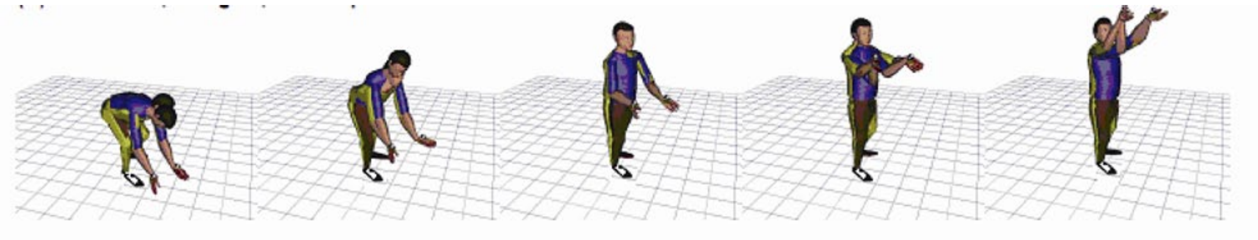
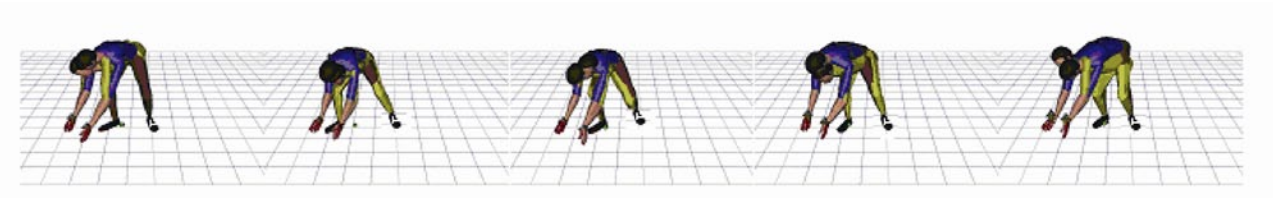
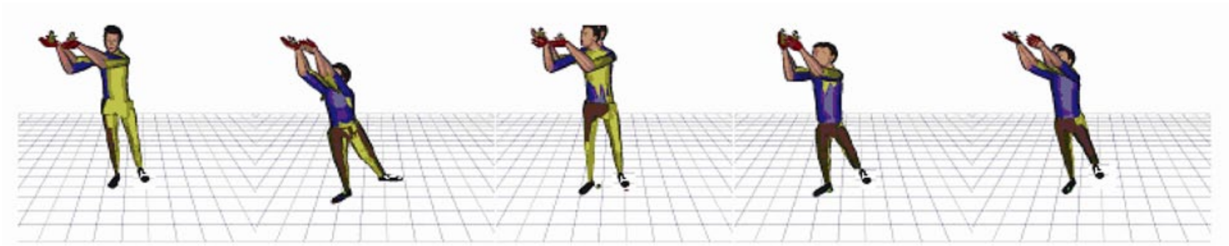


Fig. 7. Comparison of observed (yellow shirt), and predicted (blue shirt) task postures for subject 5



(a) Squatting



(b) Overhead reaching

Fig. 8. Comparison of captured (yellow shirt) and modeled (blue shirt) postures of all five subjects

5 Conclusions

(1) Based on conventional functional disability construct, a constraint-driven motion/posture model is proposed to simulate the complex interaction of human with the system within task and disability constraints. By reproducing disabilities at three levels: effectors, kinematics and physical, the proposed model can generate optimal motion/position of the physical handicapped through task controller, kinematics controller and dynamic controller.

(2) Both empirical statistical modeling and inverse kinematics approach are applied to generate motion/posture of the physically handicapped. Motion elements are dispatched to each body component classified by 4 modules to reflect effectors constraints. Joint kinematics and dynamics optimization model are used to calculate kinematics and physical constraints.

(3) Relative importance of each joint in optimization function is decided based on the captured motion data. Neural network is built up to train the weights.

(4) The framework is tested in object transferring task context. Calculated and captured postures are simulated in Jack 6.0 to give a visual comparison. The unsatisfactory parts lie in two extreme postures bending and overreaching.

(5) Validity of the weights and simplified kinematics model with roughly estimated DOF for each joint may accounts for mismatching. The future work can focus enhancing weights by training the neural network with more samples and set up a kinematics skeleton based on careful observation of the real motion which definitely requires more DOFs for each body link and joint.

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