

# Evaluating Work Disability of Lower Limb Handicapped within a Human Modeling Framework

Yan Fu<sup>1</sup>, Xingsheng Chen<sup>2</sup>, Shiqi Li<sup>1</sup>, Jacob Gwenguo Chen<sup>3</sup>, and Bohe Zhou<sup>4</sup>

<sup>1</sup> School of Mechanical Science & Engineering,  
Huazhong University of Science & Technology, Wuhan, Hubei Province, 430074, China

<sup>2</sup> School of Physical Education, Wuhan Institute of Physical Education,  
Wuhan, Hubei Province, 430074, China

<sup>3</sup> Foxconn (Hong Hai) Technology Group, Shenzhen, 518159, China

<sup>4</sup> National Key Laboratory of Human Factors, China Astronaut Training & Research Center,  
Beijing, 100094 China

Laura\_fy@mail.hust.edu.cn

**Abstract.** An accurate disability evaluation provides good basis for job placement of the handicapped and corresponding accommodations. In this study a work disability analysis model is firstly developed to predict human performance in certain task scenarios and the disability index is finally correlated to DOF of joints, the inner joint moments, the muscle pressure around the stump. The model is made of three levels. The outcome of the third level algorithm will be reflected in digital human in simulated task scenarios. To simulate handicapped behavior, the study further presents a simulation framework to realize the above three-level model, which integrate the two kinds of constraints: task constraints and physical function constraints, reflecting on posture and motion of the digital man. To validate the modeling framework, the study used material handling task as an ex-ample. Ten male BKAs were recruited in Chinese electronic manufacturing companies. The model calculated the optimization angles and moments of knee, hip, elbow joints of healthy and unhealthy parts. The calculated results are put to biomechanical-disability spectrum to generate a weighted disability index, compared to evaluation results by an occupational therapist. Meanwhile, results were put in Jack environment and a manikin was created and compared to another manikin created by motion capture data. The matching results will validate the applicability of the proposed framework to modeling handicapped behavior.

**Keywords:** Limb handicapped, work disability, human modeling, evaluation.

## 1 Introduction

Work disability is a term, which occupational therapists use to evaluate the suitability of those handicapped in daily time and occupational situations. Human performance is the final result of disability interacting with task scenarios. 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.

Many Work disability evaluation methods directly apply function disability variables to predict the handicapped work capacity in different kinds of task contexts, but cannot predict accurately the interaction effect of body disability with task factors. In other words, function disability of may correspond to different level of work disability in different task contexts. A task-related work disability evaluation is critical for accurate prediction of handicapped performance. 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 the simulated scenario [1]. To simulate the functional ability, there are varying notions such as anthropometric data, functional ability, admissible joint angles as well as physiological data such as 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 [12] used the Smart Object framework as the physical simulator to reflect the interaction of humanoid with the environment. Safonova[13] proposed a framework simulating the anthropometric characteristics in task-specific workspaces spaces. Rodriguez[9] 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 [2] set up a database containing the movements of physically disabled people. Using this data, it is possible to display the problems that each recorded individual is expected to 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 (HUMOSIM) Framework that is intended to be extensible to most human movements of interest for ergonomics. By HUMOSIM framework, the motion and posture can be predicted based on the constraints derived from the end-effectors.

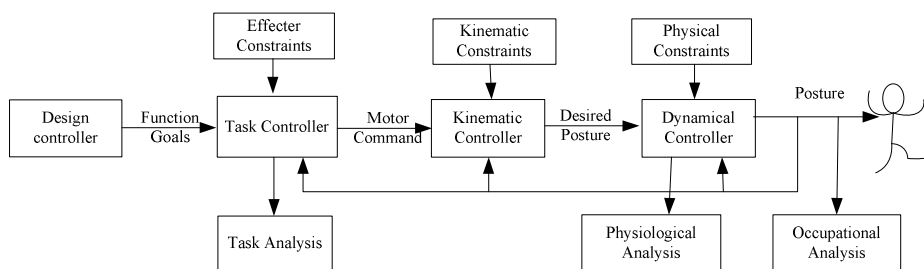
To consider the functional interaction of the disabled with the product system, the constraints not only lies in the tasks but also the variance in functional disability of the handicapped body part. The integration of physical constraints with task constraints is far more complex because of functional disability and its extended influence on adjacent body parts. This study presents a framework dedicated to integrate the two kinds of constraints and thus model the specific behavior of the physical handicapped in the virtual environment generated by the product specifications. Based on 3 levels of constraints, the model can predict the physical capacity in the dimension of

joint kinematics 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 used material handling task (squatting and reaching) as an example and compared the modeled result with that from the motion capture.

## 2 Modeling Method

Generally speaking, the functional performance in the 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 the three levels of the functional performance when human interacts with the product system (See Fig1). At task level, human biomechanical laws concluded by empirical studies are required. For example, NIOSH[12] can compute the strength maneuvering on a certain handle by the input of anthropometric parameter and handle size. Occupational analysis can be conducted in the simulation scenario. The physiological analysis deals with the forces associated with the motion, implying the information of fatigue and musculoskeletal pain. The main problem with the physiological method is the requirement of complex models to simulate the muscle function. However, to add the physiological analysis into the 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 the occupational level, the motion data collected can be connected with the individual, which makes the analysis realistic.

The constraints led to functional disability can be categorized as 3 groups: appearance (effector) constraints such as broken arm or amputation, kinematics constraints such as inaccurate pointing and less degree of freedom (DOF) of the joints and the physical constraints such as strength limits. Fig. 1 shows how the controllers operate with the interaction of the 3 kinds of constraints.



**Fig. 1.** Constraint-driven Model of Physical Handicapped Motion/Posture

There are 4 controllers in this model. Human, task 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, the design controller conveys the human function in the interaction as a goal. The data flowing into the task controller are from the task specifications. For instance, hold on a hand tool can be

translated as grasping the hand tool handle and the grasp can be transmitted to the task controller. The task controller will be constrained by the physical disability, named by effector constraints (E). For example, if the right hand of the user is dysfunctional and has weak grip strength, E is the disabled right hand. Then the resulting motor commands will be passed to the kinematics controller. This controller is responsible for generating a posture requiring for grasping the hand tool. Kinematics constraints are passed as parameters of the controller and together generate the resulting posture. The algorithm behind this controller may be function of the motor command, which will be discussed in the following sections. The resulting posture will be controlled by the dynamic controller, which can generate forces required for this posture, and produce the final posture when the user holds the hand tool. A physical simulator is enabled to generate the dynamic physics like forces and torques on the humanoid to achieve the desired posture. The physical constraints such as the strength limits are the parameters to the controller. The algorithm of dynamic controller constrained by the physical factor will be discussed in Section 3. At last the posture obtained is given back to the task controller to determine whether the function goal is achieved. When new changes were made to the 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. The constraints are the key to the physically handicapped model and motion synthesis visualizes the functional capacity of the physically disabled. And the work disability can be reflected as physiological and occupational parameters.

### 3 Motion and Posture Generation Method

To generate the motion/posture, the motion element is 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 controller based on different DOF kinematics skeletal model. (See Fig.2).

Constrained by the task variables, kinematics variables and dynamic variables, the values are to be ad-justed based on function optimization. The generation process consists of 3 main parts: (1) a set of de-sign 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). The 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 study, both joint angle and torque file are generated by optimizing cost function in kinematics and dynamic dimensions.

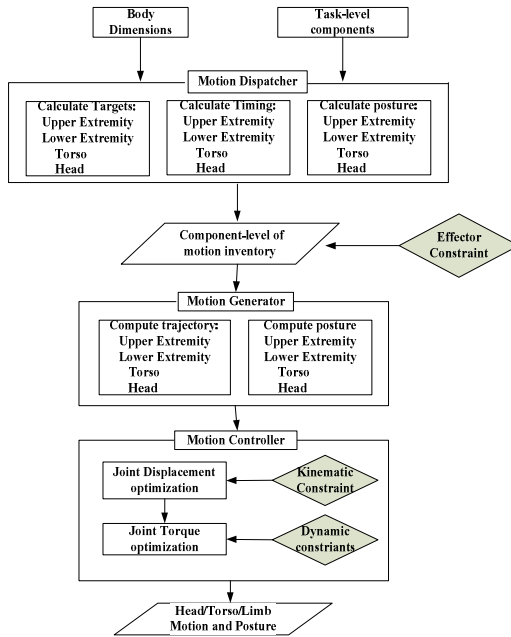


Fig. 2. Motion Generation Process

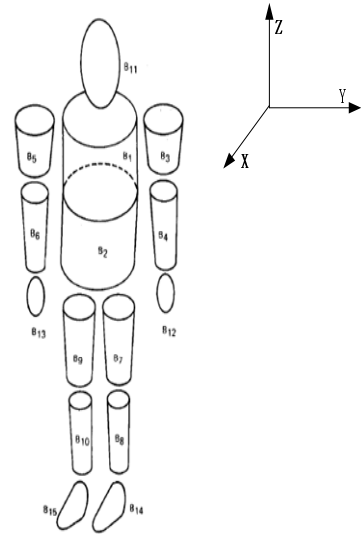


Fig. 3. Human Body of 15 Segment Links

### 3.1 Kinematics Skeletal Model

Hanavan's [13] fifteen finite segment model of the human body is applied to represent a simplified model of physical handicapped body (See Fig. 3). 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.

Degrees of freedom (DOF) of each link representing the fidelity of the 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 the spine affects the overall motion of the body. The method defines degrees of freedom by specific components in difference scenarios. In the lift 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 the objective functions of the 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:

$$F(q) = \sum_{i=1}^n w_i (q_i - q_i^N) \quad (1)$$

$$\text{St: } q_i^L \leq q_i \leq q_i^U$$

Where  $q_i^L$  is neutral position of joint  $i$ , and is selected as a relatively comfortable posture, a standing position with arms at one's side.  $w_i$  is the deviation caused by the kinematics constraints for joint  $i$  and can be determined later by feed-forward network training based on motion capture data of subjects.  $q_i^L, q_i^U$  represents the upper and lower limits of  $i$ th 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

$$\mathcal{E} = J(q_i) \dot{q}_i \quad (2)$$

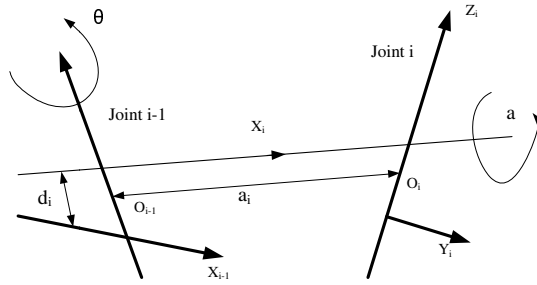
Where,  $\mathcal{E}$  is the  $m$  dimension of position vector of the end-effector and is defined by the design controller and task controller.  $J(q_i) \in T_{m \times n}$ ,  $T_{m \times n}$  is the  $m \times n$  Jacobian matrix of velocity vector,  $m$  is the dimension of the end-effector and  $n$  is DOF of joint  $i$ .  $T_{m \times n}$  can be obtained by partially differentiating to the joint speed through Eqn (3)

$$\dot{q}_n^0 = R_n^0 \dot{q}_n = R_1^0 R_2^1 \cdots R_{i-1}^i \cdots R_n^{n-1} \dot{q}_n \quad i = 1, 2, \dots, n \quad (3)$$

The Denavit and Hartenberg Representation Method (DH method) was used to sketch the coordination system of each segment link. The DH method is based on characterizing the configuration of joint  $i$  with re-spect to joint  $i-1$  by a  $(4 \times 4)$  homogeneous transformation matrix representing each joint's coordinate system as shown by Eqs (4).

$$R_{i-1}^i = \begin{bmatrix} \cos\theta & -\cos\alpha\sin\theta & \sin\alpha\sin\theta & a\cos\theta \\ \sin\theta & \cos\alpha\sin\theta & -\sin\alpha\cos\theta & a\sin\theta \\ 0 & \sin\alpha & \cos\alpha & d \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

Where  $\alpha$ ,  $\theta$ ,  $d$  and  $a$  denote the values indicated in Fig. 4



**Fig. 4.** The relation between two coordination systems with four parameters ( $\alpha$ ,  $\theta$ ,  $d$  and  $a$ )

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

$$\dot{q}_i = J^+(q_i)\mathcal{E} \quad (5)$$

$$\ddot{q}_i = J^+(q_i)[\dot{\mathcal{E}} - \dot{J}(q_i)\dot{q}_i] \quad (6)$$

Where,  $J^+(q_i)$  is the pseudo inverse of  $J(q_i)$ .

### 3.3 Joint Dynamic Optimization

Energy is the drive force of joint displacement while effort is a substitute to the 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:

$$F(q') = \sum_{i=1}^n w_i' (q_i' - q_i)^2 \quad (7)$$

To minimize:

$$\min F(\tau) = \sum_{i=1}^n w_i' |\tau_i| \quad (8)$$

St:  $F(q_i') \in F(q_i)$

$$\tau^L \leq \tau_i \leq \tau_i^U$$

$w_i'$  is the deviation caused by the physical constraints.  $\tau_i$  can be calculated through Eqn (9) according to Kim et.al.[15]

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

$m_{ik}$  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 Eqn (10):

$$M_{ik}(q) = \sum_{j=\max(i,k)}^n R_j \left\{ \frac{\partial T_j(q)}{\partial q_k} I_{ik} \left[ \frac{\partial T_j(q)}{\partial q_i} \right]^T \right\} \quad i, k, j = 1, 2, 3, \dots, n \quad (10)$$

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

## 4 Example

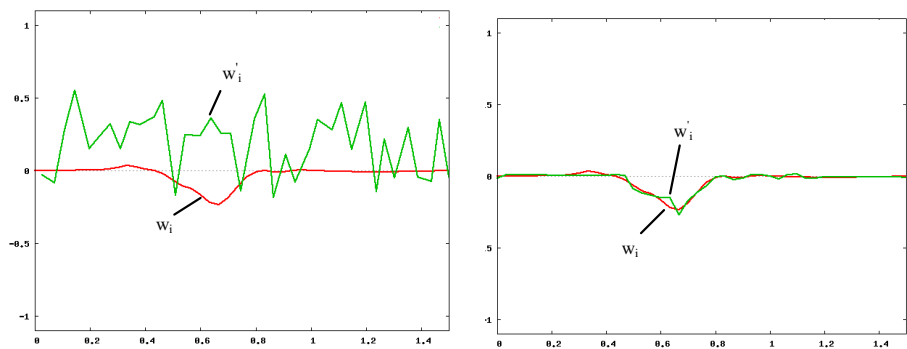
To validate the calculation model, the paper sets up an experiment of reaching and lifting task. Five under-knee prosthesis wearers on the right sides with varying body dimensions, age, and strength participated in the study. The task was bending the torso, reaching for a target in front of the subjects on the ground and lifting it up to overhead level (45 deg). The object is 2kg. 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 pre-defined body landmarks. The landmarks were used to estimate joint center locations using custom software (VICON BodyBuilder). And the 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.

Feed-forward neural network was built up to calculate the relative importance of each joint  $w_i$  and  $w'_i$ . The example extracted the values  $w_i$  and  $w'_i$  from recorded movements. The skeleton used to reproduce arm motion 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 the scenario of lifting and overreaching task, there are 20 weight groups for all joints. The learned weights of 2-DOF knee joint (healthy side) across the task time are shown in Fig 5. The limit values of each joint on different dimensions of freedom were measured. In practice, they can also be defined by medical and occupational tests.

Task simulation of subject 5 was used to explain the validity of the model. The anthropometric data of subject 5 (See Table 1) was the input of the optimization model. Subject 5 wears prosthesis on the right side.

The study chose five postures during the task to represent the whole task process. Manipulated by the weights at each corresponding time point, the model calculated the optimization angles of 12 joints. The calculated results were put into Jack environment and a manikin was created, and compared to another manikin created by motion capture data. The prosthesis foot (right) is marked with black and white. The matching results were shown in Fig. 6. In Fig. 7, the person with yellow shirts represents the observed posture by motion data capture while blue shirt stands for the posture predicted by the model.





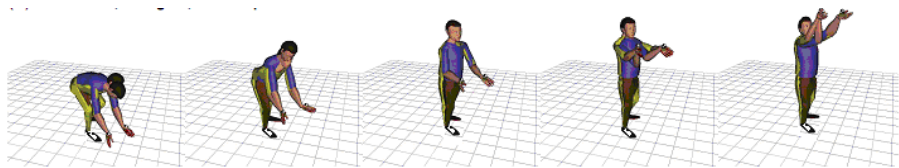
**Fig. 5.** The weights (a: X direction and b: Y direction) of the knee’s degrees of freedom over time. The red curve represents the value of  $w_i$  and the green represents the value of  $w'_i$ .

**Table 1.** Anthropometric Data and Mass Properties of Subject 5

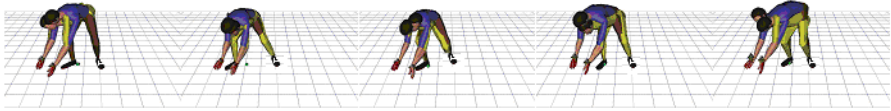
Link	Hand	Forearm	Upper arm	Torso	Upper leg	Sound leg part	Amputee
Length (m)	0.214	0.402	0.405	0.712	0.387	0.421	0.386
Mass (kg) <sup>1</sup>	0.55	2.02	1.46	28.88	10.32	10.64	3.92
M(q <sub>i</sub> )(kg•m <sup>2</sup> )	0.001	0.012	0.011	0.294	0.172	0.184	0.210

<sup>1</sup> Was calculated based on the length of each link across the same mass density except for the disabled side of leg.

As Fig. 7 shows, the yellow shirt is almost overlapped with blue shirt. The most obvious mismatching between the yellow shirt and blue shirt lies in the two extreme postures: squatting and bending to the lowest and reaching overhead. Thus, further calculations were made on the two extreme postures of all five subjects. The mismatches are shown in Fig.6. The similar mismatching can also be observed on other 4 subjects. There might be at least two reasons to explain the mismatching. The variation might lie in the weight obtained from neural network training of small number of subjects. Or physical disability causes big variance in modeling the task when the disabled body parts exert great effort to implement the task. Further study should be conducted to train weight neural network to diminish the variance across different subjects.



**Fig. 6.** Comparison of observed (yellow shirt), and predicted (blue shirt) task postures for subject 5



(a) Squatting



(b) Overhead reaching

**Fig. 7.** Comparison of captured (yellow shirt) and modeled (blue shirt) postures of all five subjects

## 5 Conclusion

This paper aimed to present a framework to evaluate work disability. By reproducing disabilities at three levels: effectors, kinematic and physical, the proposed model can optimize the position of the physical handicapped through motion and posture controller. Using object transferring as an example, the calculated results and observed results are simulated in Jack 6.0 to give a visual comparison. The unsatisfactory part of the results lies in the validity of the weights and simplified kinematics model with roughly estimated DOF for each joint. The future work can focus on the enhancement of our weight based constraint model by train the neural network with more samples and set up a kinematics skeleton based on careful observation of the real motion which definitely require more DOF for each body link and joint.

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