MEMORY-BASED HUMAN MOTION SIMULATION

by

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# TABLE OF CONTENTS

LIST OF FIGURES ........................................................................................................... IV
LIST OF TABLES ............................................................................................................. VI
LIST OF APPENDICES ................................................................................................. VII

I. INTRODUCTION ......................................................................................................... 1
   1.1 Research Background ............................................................................................... 1
   1.2 Research Objectives .................................................................................................. 5
   1.3 Research Problems .................................................................................................... 5
   1.4 Thesis Statement ....................................................................................................... 7
   1.5 Dissertation Organization .......................................................................................... 9
   1.6 References ............................................................................................................... 9

II. LITERATURE REVIEW .............................................................................................. 14
   2.1 Generalized Motor Program Theory ........................................................................ 14
   2.2. Human Movement Planning ................................................................................. 17
   2.3. Motion Simulation Models ..................................................................................... 22
   2.4 Movement Technique Representation ..................................................................... 25
   2.5 References ............................................................................................................... 28

III. INTRODUCTION ....................................................................................................... 37
   3.1 Overview ................................................................................................................... 37
   3.2 Motion Database ...................................................................................................... 39
   3.3 Root Motion Finder .................................................................................................. 40
   3.4 Movement Technique Classifier ............................................................................. 40
   3.5 Motion Modification Algorithm .............................................................................. 41

IV. MOTION MODIFICATION ALGORITHM .................................................................... 43
   4.1 Motion Modification Problem ................................................................................ 43
   4.2 Parametric Representation of Variants of a Root Motion: Solution Space Representation ............................................................................................................. 44
   4.3 Solving a Motion Modification Problem ................................................................ 47
   4.4 References ............................................................................................................... 52

V. PERFORMANCE EVALUATION OF MOTION MODIFICATION ALGORITHM ............................................................................................................. 53
   5.1 Seated Reach Motion Prediction via Motion Modification ....................................... 53
   5.2 Simulation of One-handed Whole-body Load Transfer Motions via Motion Modification ............................................................................................................. Error! Bookmark not defined.
5.3 DISCUSSION ................................................................. Error! Bookmark not defined.
5.4 References ............................................................................................................... 68

VI. MOVEMENT TECHNIQUE CLASSIFIER ............................................. 72

6.1 Introduction ................................................................................................. 72
6.2 Methods ........................................................................................................... 75
6.3 Results ............................................................................................................... 80
6.4 Discussion ......................................................................................................... 84
6.5 References ......................................................................................................... 90

VII. A CASE STUDY: LOW BACK BIOMECHANICAL ANALYSES OF MAIL
TRAY HANDLING TASKS IN USPS WORKSPACES ................................. 92

7.1 Mail Tray Handling Tasks in USPS workplaces .............................................. 92
7.2 Lowback Biomechanical Analyses and Workplace Redesign through Motion
Modification .............................................................................................................. 94
7.3 Results ............................................................................................................... 97
7.4 Discussion ......................................................................................................... 99
7.5 References ......................................................................................................... 101

VIII. CONCLUSIONS AND FUTURE RESEARCH .................................. 102

8.1 Research Contributions ................................................................................. 102
8.2 Research Conclusions .................................................................................... 103
8.3 Limitations of the Dissertation Research and Future Research Problems ....... 108
8.4 References ....................................................................................................... 113
LIST OF FIGURES

Figure 2.1. A hierarchy of motor control (From Sabes 1996) .................................................. 18
Figure 3.1. A schematic diagram of a memory-based motion simulation system............ 38
Figure 4.1. Example of segmentation of a root motion containing two joint angles. The empty squares represent the identified segment boundary points. The shapes of joint angle trajectories are represented with the strings ‘UDS’ (top) and ‘DUD’ (bottom). ............................................................... 45
Figure 4.2. Example of a variant of a root motion obtained by relocating segment boundary points and deforming the root motion accordingly. The joint angle trajectories are represented by solid and dashed lines for the root and the modified motion, respectively. Empty squares and filled circles represent the segment boundary points of the root and modified motion, respectively. ......................... 46
Figure 5.1. Experimental Setup. Arrangement of the forty-five targets with respect to a seated person......................................................... 54
Figure 5.2. Surface marker placement for motion capture and resulting kinematics linkage.................................................................................. 55
Figure 5.3. Example of motion modification (Azimuth = 180°). Root motion = reach to a target 30 cm away from the center target in the lower right quadrant (a, c). Modified motion = predicted reach to the center target (b, d). The corresponding subset of angle trajectories (e): comparison of root and modified torso joint motions (Solid curves = root motion; Dashed curves = modified motion). ........................................... 58
Figure 5.4. Fingertip speed profiles of a root motion (solid line) and eight modified motions (dashed lines). ...................................................................................... 59
Figure 5.5. Locations of the home shelf (in yellow) and the 30 target shelves. .... Error! Bookmark not defined.
Figure 5.6. Surface markers and derived internal joint centers. The filled-in squares in red represent the surface markers placed on the subjects’ body. The filled-in dots in blue, internal joint centers ................................................................. Error! Bookmark not defined.
Figure 5.7. The cross-validation scheme adopted to evaluate the prediction accuracy. ................................................................. Error! Bookmark not defined.
Figure 6.1. A five–angle, five-segment kinematic chain representing the human posture. ...................................................................................... 78
Figure 6.2. Initial posture at the start of motions and the location of the target destination ............................................................................................... 79
Figure 6.3. Three-dimensional whole-body representation of the human body and joint degrees of freedom ................................................................. 79
Figure 6.4. Box plots summarizing JCVX (a) and JCVY (b) for the stoop lifting motions. A stick figure animation of a representative stoop lifting motion is provided. .... 81
Figure 6.5. Box plots summarizing JCVX (a) and JCVY (b) for the squat lifting motions. A stick figure animation of a representative squat lifting motion is provided........ 82
Figure 6.6. Three clusters of motions formed by the K-means analysis (A, B, and C). The proximity relationships are visualized in a multidimensional scaling plot. The numbers shown in the upper left of the alphabetical letters are the movement numbers (1~20)............................................................... 83
Figure 6.7. Three motions belonging to Group A: Motion 10, 12, and 17 ............... 85
Figure 6.8. Three motions belonging to Group B: Motion 5, 7, and 16 ................. 86
Figure 6.9. Three motions belonging to Group C: Motion 2, 8, and 11. ............... 87
Figure 7.1. General Purpose Mail Cart (GPMC). .............................................. 93
Figure 7.2. A worker removing a tray from the push cart and placing it on the bottom shelf of GPMC. ................................................................. 93
Figure 7.3. Depiction of vertical adjustments made to end-point destination of task. .... 95
Figure 7.4. Differently sized digital humans .................................................... 96
Figure 7.5. Example of digital humans of identical stature lowering a mail tub to vertically adjusted end-points. .................................................. 97
Figure 7.6. Time trajectories of low back compression force associated with seven different shelf heights. ......................................................... 98
Figure 7.7. Example of digital humans with varying stature lowering a mail tub to the same destination......................................................... 98
Figure 5.8. Time trajectories of low back compression forces for workers of seven different statures......................................................... 99
LIST OF TABLES

Table 5.1. Mean TD values ................................................................. 59
Table 5.2. Subject Data ................................................................. Error! Bookmark not defined.
Table 5.3. Mean TD values ................................................................. Error! Bookmark not defined.
Table 7.1. Physical characteristics of subject ........................................... 93
LIST OF APPENDICES

Appendix A. Symbolic structure representation of human motions ........................................... 59
CHAPTER I

INTRODUCTION

1.1 Research Background

Thanks to advances in computer graphics technology and the continual enhancement of computer hardware performance, currently, in the year 2003, it is possible to rapidly render lifelike, fully articulated human figures in the virtual world. Furthermore, the existing compilation of knowledge of human anthropometry, range-of-motion, and strength provides a basis for creating digital human figures with basic human physical capabilities.

Digital humans, when integrated into traditional CAD systems, have the potential to revolutionize the way people design, build, operate, and maintain new products. Existing human CAD systems, such as SAMMIE\textsuperscript{TM}, JACK\textsuperscript{TM}, SAFEWORK\textsuperscript{TM}, and RAMSIS\textsuperscript{TM}, currently allow designers to create digital humans of different sizes and shapes in the CAD environment and let them interact with virtual prototypes of products. These software tools support ergonomic analyses such as reachability, clearance, line-of-sight, and static strength analyses. Since design prototypes can be ergonomically evaluated and necessary design changes can be made virtually, prior to building hardware prototypes, human CAD systems can reduce product development cycles and enhance the number and quality of design options (Chaffin, 2001; Porter et al., 1993; Raschke et al., 2001; McDaniel, 1990; Jimmerson, 2001). Despite its potentials, the current digital human
technology has a major limitation - it is difficult to use. In order to perform a complete ergonomic analysis on a virtual product or task, a user has to provide input data which are often difficult to obtain or generate (Chaffin, 2001). Typical input data include physical characteristics of people, products, and environments, and also human behaviors such as postures, motions, and action sequences. Among these input data, human behaviors are particularly difficult to provide, because these data tend to be complex, dynamic, indeterminate, and also neither well documented nor well understood. In order for the digital human technology to be more widely accepted in design practices, it must be provided with functions that accurately predict human behaviors (Chaffin, 2001).

One of the most desired functions of human CAD systems is the accurate simulation of human postures and motions based on a brief description of the task and the performer as the input data (Chaffin, 2001; Hsiang and Ayoub, 1994; Jung et al., 1995; Nelson, 2001; Ianni, 2001; Bowman, 2001; Thompson, 2001; Jimmerson, 2001). Such a function is important because accurate human postures and motions are the basis of many ergonomic analyses, yet they are difficult to obtain or generate.

The central problem in simulating human postures and motions is that due to the highly flexible structure of the human body, planning a posture or a motion is subjected to the redundancy or the indeterminacy problem (see Flash 1980 and Kawato 1996 for detailed review): For example, knowledge of the body dimensions of the performer and the task goal (normally represented as constraints on the hand positions and orientations) does not completely define the body posture, as an infinite number of postures can satisfy the task goal. Also, in the more general problem of planning motions, temporal patterns
of body segment motions are added to the redundancy existing in the posture planning, which increase the complexity of the problem drastically.

Currently, in practice, human figure posturing is done by direct manipulation of human figures (Beck and Chaffin, 1993). This method tends to be inaccurate and time-consuming, and has a disadvantage that a user may not perform it accurately within a reasonable amount of time unless experienced. A similar manual approach for generating motions is the key frame interpolation method: A few important key postures are first manually generated and in-between motion trajectories are computed by simple interpolations. Another manual approach of generating motions is to motion-capture actual human motor behaviors. This method guarantees realism in animation, but has the limitation that a recorded motion is only useful in the particular scenario in which the motion was originally recorded, and only represents a single person’s (actor’s) behavior.

A more sophisticated alternative to the manual approach is model-based automatic simulation of human motions. Motion simulation models generate complete movement trajectories given the input data describing the performer and the task. Several different modeling approaches have been developed in the ergonomics field: Space-time optimization models based on the minimum principle (Seireg and Avikar, 1975) were developed to simulate two-dimensional human lifting motions (Chang et al., 2001; Lin et al., 1999; Hsiang and Ayoub, 1994). Differential inverse kinematic methods, which evolved from robotics, have been utilized to predict upperbody reach motions in the linear and the angular velocity domain of human motion (Jung and Choe, 1996; Jung et al., 1995; Zhang and Chaffin, 2000; Zhang et al., 1998). Recently, a statistical modeling approach has been developed to predict human reach motions based on empirically
obtained human motions data (Faraway, 1997). These ergonomic motion simulation models have been reported to predict human reach and lifting motions accurately.

Motion simulation research has been also active in the field of human movement science. Various models have been developed to understand human motor planning and control (Alexander, 1997; Flash and Hogan, 1985; Jordan, 1990; Kawato, 1992; Kawato, 1996; Rosenbaum, et al., 1995; Rosenbaum et al., 2001, Uno et al., 1989). These models are based on different hypotheses on how the human CNS (central nervous system) represents motions and resolves redundancies, and typically aim to demonstrate feasibility of certain hypotheses or reject certain hypotheses.

Developing motion simulation models as useful ergonomic evaluation tools and understanding human movement planning do not seem to be separate issues. In fact, the two aspects could cross-fertilize each other when pursued using an integrated approach. My current dissertation research rests on the following premise:

If the actual mechanism/process behind human motion planning can be completely understood in such a way that it can be reproduced as a form of computer software or hardware, an ideal motion simulation model can be developed for computer-aided ergonomics. Conversely, if a human motion simulation model can predict human motor behaviors accurately in a wide variety of situations, and reproduce the qualities of the human motor system, the model may closely represent the actual mechanism behind the human motion planning, or at least, enhance our understanding of how human motion planning could be accomplished.
1.2 Research Objectives

The objectives of the current dissertation research are as follows:

- To review existing human motion simulation models, identify their limitations, and define research problems (A detailed literature review is provided in Chapter 2).
- To propose a novel simulation model structure that reflects the actual human system and overcomes some of the limitations of the existing human motion simulation models.
- To develop a novel motion simulation model that predicts human motions accurately in a wide variety of situations and reproduces some of the fundamental qualities of the actual human motor system.
- To experimentally confirm the soundness of the proposed motion simulation model.
- To relate the proposed motion simulation model to the current understanding of human movement planning.
- To demonstrate the utility of the model in simulating common motions of concern to job and vehicle designs.

1.3 Research Problems

Three research questions are considered in the current dissertation research. To my knowledge, the questions have not been addressed by existing motion simulation modeling efforts from both the ergonomics and the human movement science communities and represent limitations of the state of the art.
Question 1: Generality

Human activities generally consist of motions of different types. For example, in a typical manual materials handling task, a walker has to walk from one position to another, lift objects from the ground, transfer objects from one place to another, reach to different positions, etc. The human system is clearly able to plan and execute motions of different types. How can a motion simulation model simulate motions of multiple types on a single, unified platform?

Question 2: Accommodation of multiple movement techniques

In reality, people can adopt different movement techniques to perform the same manual tasks. For example, when planning a motion for a sagittal-plane lifting task, a person seems to have a choice between stoop and the squat lifting techniques. How can a simulation model identify possible alternative movement techniques for a task and predict motions based on different movement techniques?

Question 3: Expandability

A person’s movement skill set is dynamic. A person can learn new motor skills and expand his/her motion repertoire continually. How can this be implemented in a motion simulation model?

Being able to answer the above questions through developing a novel motion simulation model would greatly improve the current digital human model technology:
Answering Question 1 would provide a basis for creating complex human motor behaviors in the digital world, with more expressive power beyond the simulation of a few predetermined stereotypical motions.

Answering Question 2 would enable the consideration of the variability in human motor behaviors during computer-aided ergonomic evaluations, which the current digital human technology does not support.

Answering Question 3 would allow continual improvement in the capability of a digital human model.

Also, developing a motion simulation model that can address the above questions would enhance our understanding of the actual human motion planning, because such a model reproduces some of the fundamental characteristics of the actual system, and thus may help to explain the mechanisms that govern human motions in the actual human system.

1.4 Thesis Statement

To provide a solution to the posed research problem, the present study proposes a novel motion simulation model structure. This novel model structure is inspired by the Generalized Motor Program Theory (Schmidt and Lee, 1999). The main idea is to introduce the concept of ‘memory’ in motion simulation modeling. According to the Generalized Motor Program (GMP) Theory, the human system stores the templates of motions in memory and reuses them to plan motions for different tasks through parameter manipulation. This type of memory-based system is able to address the three questions
posed above because the memory can store different types of motions, different movement techniques, and be expanded and updated continually.

The thesis statement is:

“By having a memory in a motion simulation model that stores movement patterns (joint kinematics) and reusing the stored movement patterns through generalization and modification, it is possible to 1) predict various human motions accurately on a single, unified platform, 2) identify and utilize alternative movement techniques to predict human motions associated with a manual task, and 3) let the motion simulation system continually learn new motor skills.”

To accomplish the tasks outlined above, a general model structure termed Memory-based Motion Simulation (MBMS) model was first developed. The model structure represents the idea in the thesis statement. The model structure consists of four basic components - a memory (motion database), a motion search and retrieve engine, a motion modification algorithm for generalizing and modifying motion patterns, and a movement technique classifier for identifying alternative movement techniques. Individual components of the MBMS model structure are developed. The soundness of the motion modification algorithm and the movement technique classifier are tested experimentally, and a demonstration of its utility is provided.
1.5 Dissertation Organization

This dissertation is divided into eight chapters. Chapter 1 contains the research background, the research problem, and the thesis statement of this dissertation. Chapter 2 contains background material on ergonomic motion simulation models, different hypotheses on human motion planning, and the Generalized Motor Program Theory. Chapter 3 presents the concept and the structure of the Memory-based Motion Simulation model. Chapter 4 presents the detailed description of the motion modification algorithm. In Chapter 5, via two experimental validation studies, the performance of motion modification algorithm is evaluated. Chapter 6 presents methods for representing and identifying alternative movement techniques. Chapter 7 presents a case study in which the proposed Memory-based Motion Simulation model was used to solve actual design problems. Finally, Chapter 8 summarizes the findings and the limitations of the current dissertation, and poses future research problems.

1.6 References


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CHAPTER II
LITERATURE REVIEW

2.1 Generalized Motor Program Theory

The human neuromusculoskeletal system has many independently controllable variables called degrees of freedom, which are manifested at multiple different levels: At the gross whole-body level, the human body could be modeled as a robot-like linkage system consisting of 40 – 200 joint rotational degrees of freedom. Around each body joint, there are multiple muscles acting on it. Each muscle, in turn, is made up of hundreds to thousands of motor units which need to be controlled to execute an action.

Despite the fact that all these degrees of freedom must be controlled by the human neuromusculoskeletal system to execute motions, people do not seem to be aware of the actions of particular muscles or motor units involved, let alone consciously plan them. Instead, our experience tells us that people seem to think only about the movement goal and the movement technique. The Russian neurophysiologist Bernstein (1967) argued that it may be impossible for the central nervous system (CNS) to consciously control all of the low-level degrees of freedom separately because even planning simple movements would become too complex in this control scheme.

How does the CNS control degrees of freedom? Many researchers suggested that some structure, subordinate to the executive, may exist to organize coordination of the separate degrees of freedom. These theoretical structures were called motor programs
(Brooks, 1979, 1986; Keele, 1968, 1986a; Lashley, 1917; Schmidt, 1975b, 1988; Grillner 1975; Henry and Rogers 1960; Rosenbaum 1991; Weiss 1941). With motor programs, the movement planning problem becomes simplified, because the executive only needs to select an appropriate motor program and execute it as opposed to controlling tens of thousands of degrees of freedom simultaneously and independently.

In its earlier view (before the 1970’s), a motor program was portrayed as a set of neural commands to muscles that defines a particular pattern of action. In this view, for every possible action, a separate motor program must exist (MacNeilage, 1970). This raises two problems (Schmidt, 1988): Firstly, it is undesirable and probably impossible to store a countless number of motor programs in the long-term memory (the storage problem). Secondly, such a system cannot explain how people make new movements (the novelty problem).

In order to resolve the storage and the novelty problems, Schmidt (1975, 1976) proposed that a programmed action could be generalizable across certain dimensions. The main ideas in this generalized motor program (GMP) theory (Schmidt, 1975; Schmidt, 1986; Schmidt and Lee, 1999) can be summarized as:

- Motor programs stored in memory are responsible for the production of motion patterns, expressed in both space and time,
- Certain aspects of the motion pattern, such as overall duration or overall amplitude, are easy to change and are called parameters, and
- Other aspects, such as order of elements, phasing (relative timing), and relative amplitude are almost completely fixed from response to response and are called invariant features.
The invariant features are fundamental to motor programs and are organized and structured in memory. Motions generated from a common motor program are thought to exhibit similarly shaped space-time trajectories in certain kinematic/kinetic domains, although fine details are different from one trial to another.

The initial version of the GMP assumed that movement patterns could be linearly scaled in both duration and amplitude. According to Schmidt et al. (1998), other types of scaling could have been considered, but linear scaling was favored because of its simplicity. Experimental studies has shown that in fact, many rapid human actions exhibit linear scalability (Terzuolo and Viviani, 1979, 1980; Carter and Shapiro, 1984; Schmidt et al., 1985; Shapiro, 1978; Summers,1977). However, many counterexamples (see Getner 1987 for a review) have shown that relative timing almost always deviates from a perfect linear scalability. Especially, when skills contain environmentally determined modifications during the action, such as an open-loop, distance-covering phase (governed by the GMP, presumably) followed by a closed-loop, homing-in phase responsive to sensory information during the action, linear scalability is not exhibited (Schmidt et al., 1998; Beek, 1992). Schmidt et al. (1998) argued that no strong reason actually exists to assume that all actions are linearly scaled. For example, actions could scale nonlinearly, with certain portions of the actions changing their durations differently than others. In line with this, Kanatani-Fujimoto et al. (1997) suggested a local proportional scaling method to represent variations of movements governed by a GMP. In this method, different portions of a movement pattern are scaled linearly in both amplitude and duration with different scaling factors.
As a means of analyzing movement patterns to identify motor programs, scaling and segmentation of movement data have been utilized: Gielen et al. (1985) studied aimed arm movements of varying movement amplitude and duration, and found that velocity and acceleration profiles of the different motions coincided almost perfectly after appropriate time and amplitude scaling. Based on the result, it was suggested that a common generalized motor program governed the studied movements. Studies adopting scaling of kinematic movement data include Latash and Gottlieb (1991), Viviani and Terzuolo (1980), and Zelaznik et al. (1986). Segmentation of movement data has been used to define temporal elements of motions (Kelso and Shoner, 1988; Fagard and Wolff, 1991; Keele and Ivry, 1987; Getner, 1987; Schmidt, 1985; Schmidt, 1986; Kanatani-Fujimoto et al., 1997). Kinematic landmarks in the movement data, such as maximum, minimum, or zero crossings, were used for segmentation.

2.2. Human Movement Planning

2.2.1. Movement Control Hierarchy

As mentioned in the previous section, in order to plan a movement to achieve a task, the human neuromusculoskeletal system must control degrees of freedom manifested at many different levels – joints, muscles, motor neurons, etc. Regardless of this multilayered nature of the movement planning, ultimately the system has to deal with the lowest level of degrees of freedom, i.e., a myriad of neural motor commands to muscle fibers to execute a movement.
Greene (1972) suggested that at the highest level of the system, the global aspects of the movement are represented in the form of a goal. The control is passed down through progressively lower levels until all of the particular decisions about which motor units to fire are defined at the muscle level. The higher levels in the system do not have any direct control over muscle contractions – they only have control over adjacent levels of control that eventually result in those contractions.

Many researchers theorized that the control of human movement is hierarchically organized (Bernstein, 1967; Saltzman, 1979; Hollerbach, 1983). According to Hogan and Winters (1990), the notion of hierarchical control is an implicit assumption in most of current movement control research. The motor program concept (Schmidt and Lee, 1999) is also related to the hierarchical control: an executive and a program represent higher and lower levels, respectively. Since our memory-based motion simulation model is also located within the framework of the hierarchical movement control, the movement control hierarchy is discussed in here.

In order to illustrate the hierarchy in the human movement planning and categorize various models within this framework, the hierarchy diagram provided by Sabes (1996) is adopted here (Figure 2.1).

![Figure 2.1. A hierarchy of motor control (From Sabes 1996).](image-url)

In the strictly hierarchical movement planning scheme shown above (Figure 2.1), the human system is assumed to first conduct task level planning (Module A in Figure...
2.1). The CNS defines the goal of the task in terms of externally imposed constraints: For example, in a reach task, specifications of the initial and the final fingertip positions would define the task. Once the movement goal is defined, the goal is translated into the desirable trajectories of the end-effector by the Cartesian trajectory planner (Module B). The planned Cartesian trajectory then is input into the joint trajectory planner (Module C). The joint trajectory planner generates a set of joint angle trajectories that attains the end-effector trajectory from Module B. At the next level, the joint torque planner (Module D) plans a set of necessary joint torque profiles over time to attain the joint kinematics generated by Module C. The next level of the hierarchy then has to compute the neural commands to generate muscle activities (Module E). Finally, the musculoskeletal system generates motions following the physics rules.

One apparent advantage of the hierarchical planning scheme is modularity: Each level must only solve the small part of the overall problem, without worrying about the details of the levels above or below. Each level of the hierarchy is subordinate to its predecessor, but otherwise independent of the rest of the computational machinery of control. This modularity simplifies the control of degrees of freedom.

The above hierarchical model provides a framework for characterizing and categorizing various models of human movement planning, and also for proposing new ones. Various models of human movement planning are concerned about part of the hierarchy, and in fact, many deviate from the strict hierarchical model. Of particular interest is the controversy related to Module B and C. The key question is whether or not the joint trajectory planning is subordinate to the Cartesian endpoint trajectory planning. A series of movement analysis studies suggested that the joint trajectory planning is
subordinate to the Cartesian endpoint planning (Morasso, 1981; Soechting and Lacquaniti, 1981; Abend et al., 1982). Also many predictive models of movement planning (Hogan, 1984; Flash and Hogan, 1985; Jordan et al., 1994; Jung et al., 1995; Jung and Choe, 1996; Zhang et al., 1998; ; Zhang and Chaffin, 2000) are based on this hypothesis. The opposing view is that trajectory planning originates with the joint level description and therefore, Module B and C should be combined or B should be discarded (Soechting and Lacquaniti, 1981; Soechting and Terzuolo, 1986; Kaminsky and Gentile, 1986; Cruse, 1986; Flanagan and Ostry, 1991; Faraway, 1997; Rosenbaum et al., 1995; Rosenbaum et al., 1999; Park et al., 2001).

Another perspective is that trajectory planning is linked to the dynamics of the arm, and in fact, Modules B through D must be combined (Uno et al., 1989; Hsiang and Ayoub, 1994; Lin et al., 1999; Chang et al., 2001). A more extreme postulation is the equilibrium point hypothesis (Bizzi et al., 1976, Feldman 1986, Bizzi et al., 1992): Movements can be controlled merely by changing the equilibrium point of the actuator’s musculature; the spring-like neuromuscular dynamics (viscoelastic properties of muscle) will take care of the rest. In this view, Module A and E are directly coupled without needing the intermediate modules B, C, and D.

2.2.2 Principles of Movement Planning

In the hierarchical movement planning scheme shown in Figure 2.1, the computational problem is ill-defined or underconstrained at every step. For example, a Cartesian hand trajectory can be attained by an infinite number of sets of the joint angle
trajectories. Also, a joint torque trajectory can be attained by an infinite number of possible combinations of muscle force trajectories.

Knowing that the CNS plans a particular aspect of the movement does not tell us how it chooses the plan, how it deals with the system’s redundancies. The solution to such problems usually requires an extra criterion which is used to choose between the infinite solutions to the problem (Sabes, 1996). This method is called optimal control (Kirk, 1970).

Nubar and Contini (1961) pioneered in the optimization approach by proposing the minimum principle for muscular effort. The minimum principle states that a person determines his/her motion or posture in such a way that the total muscular effort be minimized. The optimal control concept has been applied to the modeling of movement planning in many modeling studies: Hogan (1984) posited that the CNS would try to achieve maximally smooth rotations of a single joint by minimizing the integral of the squared rate of the change of joint acceleration, or jerk. Flash and Hogan generalized this minimum jerk model for the multijoint movements. Nelson (1983) proposed the minimum energy concept. Hasan (1986) proposed the minimum effort model. Uno et al. (1989) suggested the minimum change in joint torque. These models were reported to account remarkably well for simple arm movement trajectories.

A popular approach in modeling the principle of human movement planning is to use the data-driven fitting models. Cruse (1986) and Bruwer and Cruse (1990) used nonlinear statistical methods to fit a cost function to the data. Jung and Choe (1996) and Zhang et al. (1998) took a similar approach. Faraway (1997) developed a purely statistical, functional regression model to model the dynamic human movement
trajectories. This method is distinguished from the rest, as it does not assume any underlying cost or objective functions.

2.3. Motion Simulation Models

2.3.1 Ergonomic Motion Simulation Models

Various simulation models for predicting human motions have been developed for ergonomic applications (Hsiang and Ayoub, 1994; Jung et al., 1995; Jung and Choe, 1996; Faraway, 1997; Zhang et al., 1998; Lin et al., 1999; Zhang and Chaffin, 2000; Chang et al., 2001).

Hsiang and Ayoub (1994), Lin et al. (1999), and Chang et al. (2001) developed space-time optimization models to simulate two-dimensional human lifting motions. In their models, the human body was represented as a five-segment linkage system and joint angle-trajectories were modeled as polynomial time functions. Initial and final postures of the to-be-predicted motion were assumed to be given as input data for the simulation, and the simulation problem was defined as finding realistic joint angle trajectories that connect the initial and the final postures. The models predict lifting motions by minimizing biomechanical stress measures based on the premise that people plan lifting motions so as to minimize biomechanical stresses imposed on their body.

Differential inverse kinematic methods from robotics have been utilized to predict upperbody reach motions (Jung et al., 1995; Jung and Choe, 1996; Zhang et al., 1998; Zhang and Chaffin, 2000). The primary goal of this line of research is to model how the infinitesimal movement of the hand (or end-effectors in general) in the Cartesian space
translates into the infinitesimal rotational movements of joints. In order to resolve the redundancy in this hand-to-joint mapping, kinematic optimizations have been used: Jung et al. (1995) considered the minimization of the deviations of joint angles from their neutral positions. Jung and Choe (1996) minimized an experimentally developed body posture discomfort function. Zhang et al. (1998) and Zhang and Chaffin (2000) modeled the hand-to-joint mapping using a weighted pseudoinverse. The weight values were determined from real human motion data via simulated annealing and were regarded as representing the redundancy resolution strategy in human reaches. These differential inverse kinematic models all assume that the hand motion trajectory over the entire period of motion is given as input data for the simulation either from a pre-model or real motion data.

Faraway (1997) developed a statistical method for predicting human reach motions. In his approach, a functional regression model was fitted to a large set of real human reach motions. Given input data such as the performer’s stature, age, gender, etc., and the reach target location, the regression model predicts the ‘average’ joint angle trajectories and also the confidence envelopes associated with them. The model does not guarantee the end-effector’s arrival at the intended target locations because of the statistical errors inherent in regression-based predictions, and therefore, final postures of predicted motions need to be rectified (Faraway et al., 1999).

The existing ergonomic motion simulation models described above are limited in three ways: Firstly, each one of the existing models only predicts a specific type of motions and does not provide a single unified framework in which various human activities can be simulated (the generality problem). Secondly, they are not able to reflect
intra- and inter-subject variability in human motions at the level of movement techniques during motion simulation (the problem of multiple movement technique accommodation; See Section 2.4 for further descriptions). Thirdly, they do not have a capability of learning new motor skills continually over time (the expandability problem). The current dissertation research aims to provide solutions to these problems.

2.3.2 Motion Editing

Simulating realistic human movements has been an important research topic in computer graphics, as it has many applications such as animation movie making and computer game development. The most direct approach of implementing realistic human motions in computer is to record motions performed by people in motion-capture experiments and replay them. Although motion capture guarantees realism, it has one serious limitation that a recorded motion is only useful in the particular scenario in which the motion was captured. With changes in the scenario, the motion capture process has to be repeated.

Recently, a series of computer algorithms has been developed, which aims to overcome the limitation of motion capture (Witkin and Popović, 1995; Bruderlin and Williams, 1995; Popović and Witkin, 1999; Gleicher and Litwinowicz, 1998; Gleicher 1998; Choi and Ko, 2000). These algorithms take an existing motion sample as the input data and change it to meet new constraints or impose new qualities: Bruderlin and Williams (1995) applied signal processing techniques to alter the qualities of existing motion data. Gleicher and Litwinowicz (1998) used the displacement mapping technique to alter joint angle trajectories of existing motion data to meet new position constraints.

The Memory-based Motion Simulation (MBMS) Model proposed in this dissertation research is similar to the above motion editing techniques in that it also utilizes existing motion samples to derive new ones. However, the MBMS model differs from these motion editing techniques in its main objective: It attempts to provide a model of human motion planning as opposed to merely serving as a computer algorithm that generates computer game or movie quality animations. For this reason, the MBMS has a theoretically based model structure (Chapter 3) and a motion representation technique (Section 4.2) based on theories and observations from earlier studies in the motor control and movement science areas.

2.4 Movement Technique Representation

When planning a motion to perform a goal-directed manual task, people often seem to have a choice among qualitatively different movement techniques. Some examples are as follows:

- One can perform a sagittal-plane lifting task adopting either the stoop or the squat lifting technique,
o To scratch the back of neck with the right hand, one could reach across the front side of the torso and around the neck counterclockwise, or reach along the right side of the neck,

o One can rotate a knob using either the hand or both the hand and the forearm.

Movement techniques are often referred to as movement strategies (Zhang et al., 2000), styles, or modes (Burgess-limerick and Abernethy, 1997a). The term ‘technique,’ however, seems to be used most frequently.

Alternative movement techniques have been of interest mainly in ergonomic studies of sagittal-plane lifting, because different lifting techniques were hypothesized to cause different biomechanical, physiological, and psychophysical consequences (Straker, 2003). In fact, many previous studies attempted to find a ‘correct’ movement technique for lifting training: See van Dieën et al. (1999), Straker (2003), and Burgess-Limerick (2003) for detailed reviews. Classification schemes for defining lifting movement techniques were developed, most of which were qualitative (Whitney, 1958; Lindbeck and Arborelius, 1991; Pokorny et al., 1987). Recently, quantitative indexes were developed to objectively describe lifting techniques: Burgess-Limerick and Abernethy (1997b) developed an index to describe the initial posture of a lifting motion in terms of the ratio between knee flexion and the sum of ankle, hip, and lumbar flexions. This index has a relatively large value for a squat lift and a small value for a stoop lift. Zhang et al. (2000) developed a lifting strategy index that quantifies the relative contributions of the back and the leg joint angular velocities to the linear shoulder velocity through the use of a
pseudoinverse differential inverse kinematics technique and an enumeration search process.

Unlike sagittal-plane lifting, for most manual tasks, alternative movement techniques are not well studied. Furthermore, no previous studies seem to have attempted to provide a generic quantitative method for defining alternative movement techniques for general manual tasks. This is problematic in movement related studies in which variability in human motions should be accounted for, such as ergonomic job analyses and redesigns: Different movement techniques could lead to different biomechanical, physiological, and psychophysical consequences, let alone different spatial clearance requirements. Therefore, without considering alternative scenarios, ergonomic job analyses and redesigns would lead to only limited conclusions and partially valid solutions.

Identifying alternative movement techniques is also important in human motion simulation which is the main focus of the current dissertation research: Existing motion simulation models predict motions mostly via optimization (Chang et al., 2001; Hsiang and Ayoub, 1994; Lin et al., 1999) or through empirically developed parametric statistical models (Faraway, 1997). Many previous studies showed that optimization can be used to predict a possible optimal human behavior, but this approach does not seem to predict variability in human motions at the level of movement techniques. Empirical models tend to predict motions in terms of average and variance. Without separating alternative movement techniques, an ‘average’ motion, however, could easily become a meaningless one: For example, averaging the two movement techniques for scratching the back of the neck, ‘reach across the front side of the torso and around the neck.
counterclockwise’ and ‘reach along the right side of the neck,’ produces an infeasible motion with self-collision. Identification of alternative movement techniques, therefore, is necessary for enhancing models’ prediction capabilities. To respond to this need, the current dissertation research presents a novel quantitative method for representing movement techniques and a classification approach based on it (Chapter 6).

2.5 References


CHAPTER III

INTRODUCTION

The literature review in Chapter 2 provided theoretical foundations of human motion planning research and also described existing human motion simulation models. The existing simulation models have critical limitations which define research problems for this dissertation research: Namely, the generality problem, the multiple movement technique problem, and the expandability problem. To provide an answer to these research problems, I propose a novel motion simulation model termed Memory-based Motion Simulation Model. The purpose of Chapter 3 is to describe the structure of the Memory-based Motion Simulation Model and the model’s four key components.

3.1 Overview

An MBMS system is composed of four elements: A motion database, a root motion finder, a movement technique classifier, and a motion modification algorithm, as shown in Figure 3.1.
The root motion finder then searches the motion database for the existing motion samples that closely match the input scenario. The selected motions are called root motions. A movement technique classifier analyzes the root motions to determine if there exist qualitatively different motion techniques among the root motions. If so, the system forms groups of root motions according to the movement techniques and informs the user of the existence of alternative movement techniques. Finally, the motion modification algorithm selects a root motion from each group and adapts it to meet the...
input scenario in a way that preserves the fundamental kinematic characteristics of the root motion. In what follows, each component of the MBMS system is described.

### 3.2 Motion Database

A motion database is a collection of real human motions that are recorded from motion capture experiments. Each motion in the motion database is represented as a set of joint angle trajectories. Each motion is also associated with a motion scenario. A motion scenario is composed of a set of attributes that describe the performer and the task involved in a motion. The performer attributes include stature, body weight, age, gender, etc. The task attributes include motion type, goals of the motion represented as a set of positions and orientations (e.g. initial and final fingertip positions of reaches), hand-held object characteristics, etc.

At the HUMOSIM (Human Motion Simulation) laboratory, more than 60,000 motions have been recorded since 1998 to construct a motion database. The collected motion data cover various motion types relevant to engineering design, including:

- Upperbody reach motions in a vehicle and in industrial seated workplaces,
- One-handed cylindrical hand load transfer motions in standing and seating postures,
- Two-handed box transfer motions in standing and sitting postures, and
- Two-handed box transfer motions in standing postures with high and low barriers.
3.3 Root Motion Finder

Given an input simulation scenario, the root motion finder searches the motion database to find root motions whose scenario closely matches the input simulation scenario. In doing so, a root motion selection rule is necessary. We consider the following root motion selection rule for simulating goal-directed motions:

Select every motion X in the motion database that satisfies the following conditions:

- X’s motion type must be identical to the input motion type.
- \[ \frac{\text{Initial end-effector position of } X}{\text{Initial end-effector position in the input}} - \frac{\text{Initial performer's stature of } X}{\text{Initial performer's stature in the input}} \leq \alpha \]
- \[ \frac{\text{Final end-effector position of } X}{\text{Final end-effector position in the input}} - \frac{\text{Final performer's stature of } X}{\text{Final performer's stature in the input}} \leq \alpha \]

In the above rule, \( \alpha \) is a user-specified threshold, and its maximum value can be determined by testing the prediction (extrapolation) capability of the motion modification algorithm (Chapter 5) with a set of sample motion data.

The above rule is a generic form, and could be modified according to specific needs in different simulations. For example, it is possible to consider the age and the gender of the performer and construct a database query in addition to the above rule.

3.4 Movement Technique Classifier

When performing identical movement task, people often seem to adopt qualitatively different movement techniques. One example is seen in the two alternative movement techniques used in sagittal-plane lifting motions: The ‘stoop’ versus the ‘squat’ technique. Alternative movement techniques could result in different biomechanical consequences
and be subjected to different spatial constraints, and therefore, in ergonomic motion simulations, it is essential to be able to predict human motions based on alternative movement techniques.

The MBMS model structure enables considerations of alternative movement techniques in simulating motions, as it can find multiple root motions for a given input simulation scenario. A movement technique classifier analyzes the root motions to determine if there exist qualitatively different motion techniques among the root motions. A quantitative index termed joint contribution vector (JCV) was developed to represent motions’ underlying movement techniques based on the assumption that the movement technique underlying a motion can be quantitatively described by computing contributions of individual joint rotations to the achievement of the movement task goal (See Chapter 6 for a detailed description). Once root motions are represented in JCV, by applying a statistical clustering method on the JCV data, it is possible to lump them into clusters that represent distinct movement techniques.

Once alternative movement techniques are found, the user can understand the extent of variability in movement techniques, and proceed to the simulation of motions for the input simulation scenario based on different movement techniques. The movement technique classifier is described in details in Chapter 6.

### 3.5 Motion Modification Algorithm

A root motion is selected such that its motion scenario closely matches the input simulation scenario. However, most likely a root motion will not exactly satisfy the input scenario. For example, in reach simulation, a root motion’s final fingertip position may
not be at the intended target location specified in the input. A root motion, therefore, must be adapted to the input scenario.

A motion modification algorithm (MMA) has been developed to adapt a root motion to satisfy the following types of new constraints:

- New initial hand (or fingertip or hand-held object) position and orientation, and
- New final hand (or fingertip or hand-held object) position and orientation.

The motion modification algorithm derives a parametric expression of a root motion’s possible variants in the angle-time domain and adjusts the parameter values such that the new modified motion satisfies the input simulation scenario, while retaining the root motion’s overall angular movement pattern. Detailed description of the algorithm is provided next in Chapter 4.
CHAPTER IV
MOTION MODIFICATION ALGORITHM

The purpose of Chapter 4 is to provide a detailed description of the motion modification algorithm, which is a central component of the Memory-based Motion Simulation System.

4.1 Motion Modification Problem

Three types of input data are assumed to be given to simulate a motion via motion modification: 1) anthropometric body segment dimensions, \( \mathbf{L} = [I, \ldots, I_L] \); 2) the description of the task goals in terms of initial (\( \mathbf{E}_I \)) and final (\( \mathbf{E}_F \)) location and orientation of the end-effector; and 3) a root motion given as a set of joint angle trajectories, \( \mathbf{\hat{\theta}(t)} = [\hat{\theta}_1(t) \ldots \hat{\theta}_J(t)]^T \), where \( j \) is the index for \( J \) body joint degrees of freedom (\( j = 1, \ldots, J \)) and \( t \) represents time in \([0, T]\).

The output motion to be generated is a modification of \( \mathbf{\hat{\theta}(t)} \) denoted as

\[
\mathbf{\tilde{\theta}(t)} = [\tilde{\theta}_1(t) \ldots \tilde{\theta}_J(t) \ldots \tilde{\theta}_J(t)]^T
\]

and must satisfy the task goals:

\[
\mathbf{F(\tilde{\theta}(0), \mathbf{L})} = \mathbf{E}_I \quad \text{(1)}
\]
\[
\mathbf{F(\tilde{\theta}(T), \mathbf{L})} = \mathbf{E}_F \quad \text{(2)}
\]

where \( \mathbf{F} \) represents the forward kinematics equation.
4.2 Parametric Representation of Variants of a Root Motion: Solution Space

Representation

Motion modification requires alterations of a root motion according to many new simulation scenarios. To do so, certain parameters are required that control changes imposed to the root motion. A parameterization scheme was developed to modify root motions in the angle-time domain.

In the present parameterization scheme, joint angle trajectories of the root motion are first processed by a motion segmentation algorithm (Park and Chaffin, 2001). The algorithm resolves each joint angle trajectory into geometric primitive segments labeled ‘U’ (monotonically increasing segment), ‘D’ (monotonically decreasing segment), or ‘S’ (stationary segment). Hence, the fundamental shape of a joint angle trajectory is described by a string of characters, and a motion is associated with a set of strings; one for each joint angle trajectory. The strings are collectively referred to as the symbolic ‘structure’ representation of the motion, as they depict how primitive motion units constitute the motion and abstract the motion’s general movement pattern. Figure 4.1 illustrates the idea, with the segment boundary points shown as small squares. The motion segmentation procedure consists of four steps:

1. Given a joint angle trajectory, the algorithm first identifies all the landmarks (extrema and saddle points) that might be segment boundary points,
2. Among all the identified landmarks, the algorithm selects meaningful segment boundary points free of noises,
3. The algorithm assigns an alphabetic symbol to each segment to describe its shape,
4. The algorithm eliminates possible redundancies in the symbolic structure representation.

A detailed description of the motion segmentation algorithm and the concept of symbolic structure representation are provided in Appendix.

![Diagram of joint angles and time]

Figure 4.1. Example of segmentation of a root motion containing two joint angles. The empty squares represent the identified segment boundary points. The shapes of joint angle trajectories are represented with the strings ‘UDS’ (top) and ‘DUD’ (bottom).

The segment boundary points are utilized as control parameters for modification. To derive a variant of the root motion, the segment boundary points are first relocated in the angle-time space. The locations of the segment boundary points of the root motion and the new locations after the relocation are denoted as \((T_i^r, B_i^r)\) and \((T_i^r, B_i^r)\) respectively where \(j\) is the index of the body joints (\(j = 1, \ldots, J\)) and \(i\) is the index of the segment boundary points (\(i = 1, \ldots, I_j\)):

\[
\tau_i^r = T_i^r + \Delta T_i^r, \text{ and }
\beta_i^r = B_i^r + \Delta B_i^r
\] (3)
A modified motion can be generated by shifting and proportionally rescaling individual segments of the joint angle trajectories of the root motion to fit the new segment boundary points. The new motion trajectory \( \hat{\theta}_j(t) \) at a given time \( t \) \((\tau'_i \leq t \leq \tau''_i)\) can be represented by:

\[
\hat{\theta}_j(t) = \beta'_j + \frac{\beta''_j - \beta'_j}{B''_j - B'_j} \left( \theta \left( T'_j + T''_j - T'_j \left( t - \tau'_i \right) \right) - B'_j \right) \text{ when } B''_j - B'_j \neq 0, \text{ and }
\]

\[
\hat{\theta}_j(t) = \beta'_j, \text{ when } B''_j - B'_j = 0
\]

An example of a variant from a root motion is illustrated in Figure 4.2.

![Diagram](https://via.placeholder.com/150)

Figure 4.2. Example of a variant of a root motion obtained by relocating segment boundary points and deforming the root motion accordingly. The joint angle trajectories are represented by solid and dashed lines for the root and the modified motion, respectively. Empty squares and filled circles represent the segment boundary points of the root and modified motion, respectively.

Possible new locations of segment boundary points \((\tau'_i, \beta'_i)\) are bound by the following constraints:

1) The new segment boundary points must not change the order of events in time:

\[ \tau''_i > \tau'_i \text{ for all } j \text{ and } i \] (Order of event constraint).
2) The new segment boundary points must not change the shape of joint angle trajectories. In other words, the shape-representing string should remain the same (Angle trajectory shape constraint).

3) The new segment boundary points must not violate the joint range of motion constraints (Joint range of motion constraint).

Also, the duration of the movements is normalized to \([0, T]\), hence, \(\tau_i' = 0\) and \(\tau_j' = T\) for all \(j\).

The parameterization scheme maps a root motion to a motion family which consists of the root motion’s possible variants. The variants retain the root motion’s properties such as the smoothness and the spatial-temporal movement patterns commonly known as invariant features of generalized motor programs (R. A. Schmidt and T. D. Lee, 1999).

### 4.3 Solving a Motion Modification Problem

To solve a particular motion modification problem, the new segment boundary point locations \((\tau_i', \beta_i')\) should be set so that the modified motion satisfies the task goal constraints stated in (1) and (2). Each equation provides at most six constraints (3 for hand position and 3 for hand orientation). However, the number of parameters to be determined (coordinates of all segment boundary points) exceeds the number of constraints and allows an infinite number of possible solutions. To resolve the redundancy problem, a minimum dissimilarity principle is proposed: Among all possible variants of the root motion that satisfy (1) and (2), one that resembles the root motion the most is selected.
The motion modification consists of a two-step iteration; The initial and final postures are iteratively modified to satisfy (1) and (2). The joint angle trajectories are modified to link the modified initial and final postures. This process is repeated until all constraints are satisfied.

4.3.1 In-between trajectory modification given new initial and final postures

The in-between trajectory modification takes a root motion and a pair of new initial and final postures as input data and modifies the root motion to fit the new terminal postures. How to determine the new initial and final postures in a way that (1) and (2) are satisfied is described in the next section (Section 4.3.2).

Each joint angle trajectory of the root motion $\tilde{\theta}(t)$ is modified individually to obtain a new joint angle trajectory, $\hat{\theta}(t)$, that links $\hat{\theta}(0)$ and $\hat{\theta}(T)$, the given initial and final joint angle values of the $j$-th joint angle trajectory of the new motion.

The parameterization scheme described in the previous section allows the problem to be defined in terms of segment boundary point location parameters. Since the new locations of the initial and final segment boundary points, $(\tau_i', \beta_i')$ and $(\tau_f', \beta_f')$, are given as $\tau_i' = 0, \beta_i' = \hat{\theta}(0), \tau_f' = T$, and $\beta_f' = \hat{\theta}(T)$, our goal is to determine the new locations of the non-terminal segment boundary points, $(\tau_i', \beta_i')$ for $i = 2, ..., (I_j - 1)$.

When $I_j = 2$, $\hat{\theta}(t)$ is completely determined by (4) from $\beta_i'$ and $\beta_f'$. However, when $I_j > 2$, the locations of the intermediate segment boundary points become indeterminate. To resolve this indeterminacy, the following minimization problem is solved:
Minimize $\int_0^T \left( \dot{\theta}_j(t) - \hat{\theta}_j(t) \right)^2 dt$  \hspace{1cm} (5)

s.t.

$\dot{\theta}_j(0)$ and $\dot{\theta}_j(T)$ are given as constants

In (5), $\dot{\theta}_j(i)$ and $\hat{\theta}_j(i)$ denote the first time derivatives of the to-be-determined and the root joint angle trajectories respectively. By solving (5), a new joint angle trajectory $\hat{\theta}_j(i)$ is found that links $\dot{\theta}_j(0)$ and $\dot{\theta}_j(T)$ smoothly and also resembles $\hat{\theta}_j(i)$ in the angular velocity domain.

Equation (5) was restated as a function of segment boundary point parameters, $\beta^i$'s and $\tau'$'s. The optimization problem was simplified by setting the occurrence times of the new segment boundary points equal to those of the segment boundary points of the root angle trajectory:

$$\tau'_i = T'_i \text{ for all } i$$  \hspace{1cm} (6)

The above simplification follows the minimum dissimilarity principle as it forces the timing of events in the modified and root joint angle trajectories to be identical. Hence, the inter-joint coordination of the root motion is retained in the new motion. With this simplification, the objective function in (5) can be rewritten as:

$$\int_0^T \left( \dot{\theta}_j(t) - \hat{\theta}_j(t) \right)^2 dt \approx \sum_{i=1}^{i_{\text{end}}} \left( (\hat{\upsilon}'_i - \tilde{\upsilon}'_i) \cdot \text{duration}_i \right) = \sum_{i=1}^{i_{\text{end}}} \left( \frac{\beta'_i - \beta^i}{T'_{i_{\text{end}}} - T'_{i_{\text{start}}} - T'_i} \frac{B'_i - B^i}{T'_{i_{\text{end}}} - T'_{i_{\text{start}}} - T'_i} \right) \left( T'_{i_{\text{end}}} - T'_{i_{\text{start}}} \right)$$  \hspace{1cm} (7)

where $\hat{\upsilon}'_i$ and $\tilde{\upsilon}'_i$ denote the average joint angular velocity during the i-th segment, and $\text{duration}_i$ denotes the time-duration of the i-th segment.
The optimal solution (βi's) that minimizes the above objective function was found to be:

\[ \beta_i' = B_i + (\beta_i' - B_i') \left( \frac{T_i - T'}{T'} \right) + (\beta_i' - B_i') \frac{T'}{T'} \]  

(8)

The above solution does not guarantee maintenance of the shape of ‘S’ segments, because the optimization problem shown in Equation (5) does not explicitly consider the angle trajectory shape constraints, and may rescale ‘S’ segments in magnitude into ‘U’ or ‘D’ segments. Hence, in order to prevent ‘S’ segments from being rescaled, the solution was slightly modified to:

\[ \beta_i' = B_i + (\beta_i' - B_i') \left( \frac{T_i - T'_{\text{U/D}}}{} \right) + (\beta_i' - B_i') \frac{T'}{T'} \]  

(9)

where \( T' \) denotes the sum of durations of all the ‘U’ and ‘D’ segments, and \( T'_{\text{U/D}} \) denotes the sum of durations of all the ‘U’ and ‘D’ segments included in \([0, T']\). The solution shown in Equation (9) rescales only ‘U’ and ‘D’ segments, and therefore, all ‘S’ segments in an angle trajectory can maintain its shape.

The solution shown in Equation (9) may still violate joint range of motion constraints and compute physiologically impossible joint angle values. For each modified joint angle trajectory \( \tilde{\theta}(t) \) (\( j = 1, ..., J \)), it is assumed that joint range of motion constraints can be expressed as the following inequalities:

\[ L_j \leq \tilde{\theta}(t) \leq U_j \]  

for 0 ≤ t ≤ T

(10)

where \( L_j \) and \( U_j \) represent physiologically possible extreme values of \( \tilde{\theta}(t) \). Equivalently, (10) can be restated as follows:

\[ L_j \leq \beta_i' \leq U_j \]  

for all \( i \)

(11)

If the \( \beta_i' \) value computed from (9) does not satisfy (11), it is corrected as follows:
If $\beta_i' < L_i$, then $\beta_i' = L_i$  
(12)

If $\beta_i' > U_i$, then $\beta_i' = U_i$  
(13)

The optimal $\beta_i'$ s from (9), (12), and (13) completely determine $\hat{\theta}_j(t)$ for $0 \leq t \leq T$ with (4).

4.3.2. Initial and Final Posture Modification

The initial and final postures of the modified motion, $\beta_i$ and $\beta_f$ (or equivalently, $\hat{\theta}(0)$ and $\hat{\theta}(T)$), must satisfy (1) and (2). (1) and (2) can be rewritten as:

$$G_i(\beta_i) = \|F(\beta_i, L_i) - E_i\| = 0$$  
(10)

$$G_f(\beta_f) = \|F(\beta_f, L_f) - E_f\| = 0$$  
(11)

Each of the above equality constraints represents an inverse kinematics problem with redundant degrees of freedom. In order to resolve the redundancy, the minimum dissimilarity principle is adopted: The new initial (or final) posture should be chosen such that it resembles the initial (or final) posture of the root motion as much as possible while satisfying the constraints.

Such new initial and final postures can be found by modifying the initial and final postures of the root motion using the following iterative update scheme:

$$\beta_{\text{new}} = \beta_{\text{prev}} - \alpha \frac{\nabla G(\beta_{\text{prev}})}{\|\nabla G(\beta_{\text{prev}})\|}$$  
(12)

where $\nabla G$ represents the gradient of the function $G$ (either $G_i$ or $G_f$) and $\alpha$ represents a step-length parameter for each update. In (12), $-\nabla G / \|\nabla G\|$ indicates the direction of infinitesimal postural change that reduces the function $G$ the greatest, and thus
approaches the state of satisfying Equation (10) or (11) with the minimum infinitesimal postural change.

Equation (12) was further modified to take into consideration the fact that different body joints contribute more or less to a particular motion. The joint with more movement in the root motion are modified more during the posture update. This assumption is implemented by introducing weighting factors:

\[
\beta_{\text{new}} = \beta_{\text{prev}} - \alpha \frac{W \cdot \nabla G (\beta_{\text{prev}})}{\|W \cdot \nabla G (\beta_{\text{prev}})\|}
\]  

(13)

where \( W = [w_i \ldots w_j \ldots w_j] \) represents weighting factors for each joints. The weighting factors are estimated by:

\[
w_j = \frac{\max(\hat{\theta}_j(t)) - \min(\hat{\theta}_j(t))}{T} \text{ where } t \in [0,T]
\]  

(14)

The initial and final posture updates continue simultaneously until both (10) and (11) are satisfied (until \( G_i \) and \( G_j \) become smaller than a small user-defined threshold). At each iteration, the entire motion can be recalculated using (9). If the current update of the initial and final postures and the recalculated motion from (9) violate any shape or joint range of motion constraint for a particular joint, the algorithm undoes the update at that particular joint so as to ensure the satisfaction of constraints and proceeds to the next iteration.

4.4 References

CHAPTER V

PERFORMANCE EVALUATION OF MOTION MODIFICATION ALGORITHM

The motion modification algorithm described in Chapter 4 provided a new method for predicting various human motions based on existing ‘root’ motions. In order to prove the utility of the algorithm as a predictive tool for computer-aided ergonomics, Chapter 5 evaluates its prediction accuracy: Motions predicted by the algorithm are compared with actual human motions obtained in motion capture experiments. Two types of motions were simulated and compared with real motions for this validation study: One-handed seated reaches (Section 5.1) and One-handed whole-body load transfer motions (Section 5.2).

5.1 Seated Reach Motion Prediction via Motion Modification

5.1.1 Motion Capture Experiment

The first experiment was designed to validate the motion modification algorithm for seated reaches with one hand. A series of seated reach motions were motion-captured. A subset of these motions was used as root motions, while the others were used for comparison with modified (predicted) motions and the prediction error quantification.

Five young and healthy adult subjects (3 females and 2 males) participated in the motion capture experiment. The mean age, stature, and body weight were 24.8 yrs, 164.6...
cm, and 55 kg, respectively. Each subject performed a series of reaches to spherical targets (Ø = 4 cm) while seated in a truck/van type seat. Each reach started from an initial seated erect posture with the right hand resting on a support located near the knee (Figure 5.1). The task consisted of reaching with the right index finger to one of nine targets distributed on an X-shaped support (Figure 5.1). Two sets of four targets were distributed on the four branches of the support 15 cm and 30 cm away from the center target located 102 cm above the ground. The target post was placed 74 cm away from the vertical body center line and at five different azimuths (0°, 45°, 90°, 135°, and 180°). For each azimuth the targets were reached in a random order; the center target was reached four times while the other targets were reached only once. The order of presentation of the azimuth was also randomized.

Figure 5.1. Experimental Setup. Arrangement of the forty-five targets with respect to a seated person.

A McReflex™ motion analysis system with six cameras was employed to capture the motions of the upper torso and right upper extremities at a sampling frequency of 25 Hz. Eight spherical reflective markers were placed on body landmarks (Figure 5.2a)
identifying the tip of index finger, the lateral styloid process at the wrist, the humeral lateral epicondyle at the elbow, the right and left acromion processes, the suprasternale, and right and left anterior-superior iliac spine (ASIS).

Figure 5.2. Surface marker placement for motion capture and resulting kinematics linkage.

The surface markers were used to derive the configuration of a five segment kinematic linkage system (Figure 5.2b)): torso, clavicle, upper arm, lower arm, and hand-finger. The method developed by Nussbaum et al. (1996) was used to determine the joint centers of rotation. To describe postures and motions, nine local Euler angles were used (3 for the torso, 3 for the upper arm, one for the lower arm and 2 for the hand).

5.1.2 Data Analysis
For each subject and each azimuth, the eight motions to the peripheral targets served as the root motions and were modified to simulate a reach to the center target. For each modification, the new task goal was defined only by the center target location without any constraint on hand orientation, since the recorded motions were unrestricted reaches. Also, as the subjects started from a consistent initial posture, this posture was used as the initial posture for the modification process. The eight modified motions were grouped into two clusters labeled ‘15cm modifications’ and ‘30cm modifications’ according to the distance between the center target and the original destination of the corresponding root motion. For each subject, each of the 40 modified motions was compared to the 4 real motions to the center target.

The prediction error associated with a comparison of a real and a predicted motion was estimated by the time-averaged distance (TD) between the predicted and real trajectories of the C7/T1, shoulder, elbow, wrist joints and the tip of the index finger:

$$\text{TD (Time-averaged Distance)} = \frac{\int_0^T \| \mathbf{X}_p(t) - \mathbf{X}_m(t) \| dt}{T}$$  \hspace{1cm} (1)$$

where $\mathbf{X}_p(t)$ and $\mathbf{X}_m(t)$ denote the predicted and the measured position of a body landmark at time t.

TD was also used to quantify the within-subject motion variability (WIMV) in repeated human motions. For each subject and each azimuth, four real reach motions to the center target were compared with one another so as to evaluate WIMV. Four reaches allowed 6 pairwise comparisons; therefore, across all subjects and azimuths 150 pairwise comparisons of real motions were made. WIMV was compared with prediction errors in order to determine if the prediction errors are acceptable when compared to the inherent
variation in repeated human motions. TD values corresponding to prediction errors in 15cm modifications and in 30cm modifications were compared with TD values for WIMV respectively, using a t-test with $\alpha = 0.05$.

In addition to the quantitative analysis of the prediction errors, fingertip speed profiles of both predicted and real motions were compared to verify the preservation of the bell shape velocity profile that characterizes reach movements (Abend et al., 1982; Morasso, 1981; Flash and Hogan, 1985; Georgopoulos et al., 1981; Soechting and Lacquaniti, 1981; Atkeson and Hollerbach, 1985).

5.1.3 Results

An example of motion modification is illustrated in Figure 5.3a-5.3e. A root motion (Figure 5.3a and 5.3c) corresponding to a target (Target 8) 30 cm away from the center target in the lower right quadrant for a 180° azimuth was modified to predict a motion to the corresponding center target (Figure 5.3b and 5.3d). Figure 5.3e illustrates three joint angle trajectories of the root and the modified motion.

Table 5.1 presents the mean TD values for the four selected joints and end-effector corresponding to, 1) the WIMV, 2) the prediction error in 15cm modifications, and 3) the prediction errors in 30cm modifications. Differences between the mean prediction error and the mean WIMV are inserted in parentheses. No statistically significant difference was found between WIMV and the prediction error in 15cm-modifications. However, differences between WIMV and the prediction error in 30cm modifications were found statistically significant for all trajectories. The largest difference was 1.3 cm for the wrist joint.
Figure 5.3. Example of motion modification (Azimuth = 180°). Root motion = reach to a target 30 cm away from the center target in the lower right quadrant (a, c). Modified motion = predicted reach to the center target (b, d). The corresponding subset of angle trajectories (e): comparison of root and modified torso joint motions (Solid curves = root motion; Dashed curves = modified motion).
Table 5.1. Mean TD values

<table>
<thead>
<tr>
<th></th>
<th>C7/T1 Joint</th>
<th>Shoulder Joint</th>
<th>Elbow Joint</th>
<th>Wrist Joint</th>
<th>Fingertip</th>
</tr>
</thead>
<tbody>
<tr>
<td>WIMV</td>
<td>1.5</td>
<td>1.8</td>
<td>3.0</td>
<td>3.8</td>
<td>4.4</td>
</tr>
<tr>
<td>15 cm modifications</td>
<td>1.6 (0.1)</td>
<td>1.6 (-0.2)</td>
<td>3.0 (0.0)</td>
<td>4.0 (0.2)</td>
<td>4.4 (0.0)</td>
</tr>
<tr>
<td>30 cm modifications</td>
<td>2.1* (0.6)</td>
<td>2.1* (0.3)</td>
<td>3.9* (0.9)</td>
<td>5.1* (1.3)</td>
<td>5.5* (1.1)</td>
</tr>
</tbody>
</table>

*Statistically significant difference from WIMV (alpha = 0.05)  
(Unit: centimeters)

Figure 5.4 presents a typical example of time and amplitude normalized fingertip speed profiles of real (solid lines) and modified (dashed lines) reach motions for four 15 cm and four 30 cm modifications. The modified motions as well as the real one exhibit very similar bell-shaped speed profiles.
5.2 Simulation of One-handed Whole-body Load Transfer Motions via Motion Modification

5.2.1 Motion Capture Experiment

The second experiment was designed to validate the motion modification algorithm for whole-body load transfer motions. A series of one-handed whole-body load transfer motions were motion-captured.

Ten male and ten female subjects covering a wide range of age, stature, and body weight levels participated in the motion capture experiment. The subject demographic information is provided in Table 5.2.

<table>
<thead>
<tr>
<th>Subject</th>
<th>M/F</th>
<th>Age (yrs)</th>
<th>Weight (kg)</th>
<th>Stature (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M</td>
<td>20</td>
<td>60.9</td>
<td>173.8</td>
</tr>
<tr>
<td>2</td>
<td>F</td>
<td>21</td>
<td>67.1</td>
<td>163.1</td>
</tr>
<tr>
<td>3</td>
<td>M</td>
<td>22</td>
<td>81.4</td>
<td>185.5</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>21</td>
<td>43.6</td>
<td>150.0</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>48</td>
<td>61.0</td>
<td>169.9</td>
</tr>
<tr>
<td>6</td>
<td>M</td>
<td>33</td>
<td>81.1</td>
<td>176.5</td>
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<tr>
<td>7</td>
<td>M</td>
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<td>59.3</td>
<td>160.5</td>
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<tr>
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<td>M</td>
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<td>95.1</td>
<td>173.3</td>
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<tr>
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<td>87.3</td>
<td>171.3</td>
</tr>
<tr>
<td>15</td>
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<td>49</td>
<td>64.3</td>
<td>166.1</td>
</tr>
<tr>
<td>16</td>
<td>M</td>
<td>48</td>
<td>70.5</td>
<td>174.6</td>
</tr>
<tr>
<td>17</td>
<td>F</td>
<td>54</td>
<td>58.0</td>
<td>160.6</td>
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<tr>
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<td>186.1</td>
</tr>
<tr>
<td>19</td>
<td>M</td>
<td>53</td>
<td>86.0</td>
<td>170.1</td>
</tr>
<tr>
<td>20</td>
<td>F</td>
<td>29</td>
<td>87.4</td>
<td>170.1</td>
</tr>
</tbody>
</table>
Each subject was asked to transfer a vertical cylindrical object from a home shelf located in front of his/her body to each of 30 target shelves. Locations of the 30 target shelves were fixed in the workspace regardless of differences in the subjects’ statures. Figure 5.5 shows the spatial arrangement of the home shelf and the target shelves.

During each trial, the subjects were allowed to move their right foot freely but asked to have their left ball of foot in contact with a fixed location on the ground. The left ball-of-foot location serves as the origin of the global coordinate system. Note: the left foot can rotate but not translate around the ball of the foot.

A custom motion capture system which utilizes both the MacReflex and the Flock-of-Birds systems was used to record the subjects’ movements. Fourteen surface markers were placed on each subject’s body (See Figure 5.6). The recording was performed with a sampling frequency of 25 Hz. Based on the recording of position and orientation data,
the internal linkage (18 links) and the 45 joint angle trajectories were derived for each motion.

Figure 5.6. Surface markers and derived internal joint centers. The filled-in squares represent the surface markers placed on the subjects’ body. The filled-in dots, internal joint centers.

5.2.2 Data Analysis

A total of 627 motions were found to be free of missing markers and other data corruptions. These motion data were used to construct a MBMS system. In order to evaluate the prediction accuracy of the motion modification algorithm, a cross-validation scheme (Figure 5.7) was devised.
626 motions

Scenario of Figure 5.7. The cross-validation scheme adopted to evaluate the prediction accuracy.

In this cross-validation scheme, a total of 627 pairwise comparisons of real and predicted motions were conducted. For each comparison, a motion was selected among the 627 motions. This motion is called a target motion and was compared with a motion predicted by the motion modification algorithm. In figure 5.7, the selected target motion is represented as a black dot. When a target motion was chosen, the rest of the motions formed a motion database, and thus, an MBMS system. Then, the scenario of the target motion (the final hand position and the height of the performer) was entered into the

Baseline: Between-subject Inter-trial Motion Variability (BIMV)

Figure 5.7. The cross-validation scheme adopted to evaluate the prediction accuracy.
MBMS system. The MBMS system searched the motion database to find a root motion that meets the following conditions:

- The performer of a root motion should be different from the performer of a target motion,
- The distance between the height-adjusted final hand positions of a chosen root motion and the target motion should be greater than 0.1 (10% of the height), and
- Among all candidate root motions in the database satisfying the above conditions, the chosen root motion should be the closest neighbor to the target motion in terms of the height-adjusted final hand position (the closest neighbor criterion).

The first condition was imposed to quantify ‘between-subject’ prediction errors. The second condition was imposed in order to prevent the chosen root motion from being too similar to the target motion. The second condition, thus, prevents the motion prediction from being too easy.

The selected root motion was modified according to the scenario of the target motion. The prediction error associated with a comparison of a real (target) and a predicted (or modified) motion was estimated by the time-averaged distance (TD) between the predicted and real trajectories of the right hand grip center and 9 body joint centers: The nine body joints used for validation were the L5/S1, SCJ, C7T1, right shoulder, right elbow, right wrist, left hip, left knee, and left ankle joints.

The between-subject inter-trial motion variability (BIMV) was estimated by comparing motions of different individuals in identical task conditions. The individuals
in comparison were almost identical in their heights (the maximum allowed stature difference was 1cm). The TD measure was used to quantify the BIMV. TD values corresponding to the prediction error were compared with TD values for the BIMV, using a t-test of the mean values with $\alpha = 0.05$.

5.2.3. Results

Figure 5.8 illustrates examples of motion modifications for whole-body hand load transfer motions: The root motion shown on the left in Figure 5.8 was modified to meet four new scenarios shown on the right.

Table 5.3 presents the mean TD values for the nine selected body joints and the right hand grip center corresponding to the BIMV and the prediction error. Differences between the mean prediction error and the mean BIMV are inserted in parentheses. No statistically significant difference was found between the BIMV and the prediction error for the left hip, L5/S1, SCJ, C7T1, right shoulder, right elbow, and right wrist joints. However, statistically significant differences were found for the left ankle, left knee, and right wrist joints, and the right grip center. The statistically significant differences indicated that the mean prediction error was smaller than the mean BIMV.

5.3 Discussion

The strong similarities between the joint angle trajectories of the root and modified motions (Figure 5.3) and the preservation of the bell-shaped velocity profile of the end-effector (Figure 5.4) show that the modification process conserves the characteristics of
the overall pattern of the root motion. In addition, the statistical analyses shown in Table 5.1 and 5.3 confirm the prediction accuracy of the algorithm.

Figure 5.8. Modifications of a three-dimensional whole-body root motion on the left according to four new task scenarios shown on the right.
In the seated reach predictions, the difference between the natural variability in repeated motions of an individual and the mean prediction error resulting from 30 cm modifications was at the most 1.3 cm. Despite a statistical significance, this difference is rather small when considering the large distance (30 cm) between the original and new destination target. This difference is negligible ($\leq 0.2$ cm) when the new destination target is located 15 cm away from the original target. Hence, these results demonstrate the robustness of the algorithm and support its capability to predict motion with accuracy almost identical to the observed variability in repeated human motions.

As for the predictions of whole-body one-handed load transfer motions, as shown in Table 5.3, the differences between the BIMV and the prediction error in TD values were small. No statistically significant difference was found between the BIMV and the prediction error for the left hip, L5/S1, SCJ, C7T1, right shoulder, right elbow, and right wrist joints. However, statistically significant differences were found for the left ankle, left knee, and right wrist joints, and the right grip center. Surprisingly, the statistically significant differences indicated that the mean prediction error was smaller than the mean BIMV, which is rather counterintuitive, because, on average, the mean prediction error must be greater than or equal to the inherent variability of human motions in identical task conditions. One possible explanation of this oddity is that in quantifying the BIMV,
subjects whose motions were under comparison had different body segment link lengths despite the closeness in stature (less than 1 cm) while in quantifying prediction errors, no such error component was involved (the predicted and the target motions were associated with identical kinematic linkages). Overall, the small differences between the BIMV and the prediction error suggest that the motion modification algorithm is able to predict three-dimensional whole-body motions accurately.

In this chapter, two types of human motions, one-handed seated reaches (Section 5.1) and one-handed whole-body load transfer motions (Section 5.2), were simulated and the simulated motions used as a basis for evaluating the prediction capability of MBMS. Although the motion modification algorithm were able to predict qualitatively (categorically) different reach and load transfer motions based on a single system, the current validation studies do not include other types of movements in workplaces and vehicles including lifting and reaches in the presence of obstacles. Therefore, validations with a wider range of movement types are still needed.

5.4 References


6.1 Introduction

When planning a motion for a goal-directed manual task, people often seem to have a choice among qualitatively different movement techniques. Some examples are as follows:

- One can perform a sagittal-plane lifting task adopting either the stoop or the squat lifting technique,
- To scratch the back of neck with the right hand, one could reach across the front side of the torso and around the neck counterclockwise, or reach along the right side of the neck,
- One can rotate a knob using either the hand or both the hand and the forearm.

Movement techniques are often referred to as movement strategies (Zhang et al., 2000), styles, or modes (Burgess-limerick and Abernethy, 1997a). The term ‘technique’ is adopted here for the sake of consistency.

Alternative movement techniques have been of interest mainly in ergonomic studies of sagittal-plane lifting, because the stoop and the squat lifting techniques were hypothesized to procreate musculoskeletal injuries differently: See van Dieën et al. (1999) for review.
Classification schemes for categorizing lifting motions were developed, most of which were qualitative (Whitney, 1958; Lindbeck and Arborelius, 1991; Pokorny et al., 1987). Recently, quantitative indexes were developed to objectively describe movement techniques: Burgess-Limerick and Abernethy (1997b) developed an index to describe the initial posture of a lifting motion in terms of the ratio between the knee flexion and the sum of ankle, hip, and lumbar flexion. The index has a relatively large value for a squat lift and a small value for a stoop lift. Zhang et al. (2000) developed a lifting strategy index that quantifies the relative contributions of the back and the leg joint angular velocities to the linear shoulder velocity. The index value is computed through an enumeration search process.

Unlike sagittal-plane lifting, for most manual tasks, movement techniques are not well classified and are mostly unknown. This is problematic because it seems crucial to understand alternative movement techniques comprehensively in ergonomic task evaluations, because in performing the same manual task, alternative movement techniques could lead to different consequences in biomechanical stresses and spatial constraints. Without considering alternative scenarios, conclusions from an ergonomic analysis could be limited.

Despite the importance of considerations of alternative movement techniques, the existing motion simulation models do not have a capability of predicting motions based on alternative movement techniques: As summarized in Chapter 2, current motion simulation models predict motions via optimization (Chang et al., 2001; Hsiang and Ayoub, 1994; Lin et al., 1999) or through empirically developed parametric statistical models (Faraway, 1997). Optimization could predict a possible human behavior, but it
does not seem able to predict the variability in movement techniques by finding more
than one optimal motion. Empirical models tend to predict motions in terms of an
average and a variance. An ‘average’ motion, however, could become a meaningless
one: For example, averaging the movement techniques for scratching the back of the neck
would produce an infeasible motion with self-collision.

To identify alternative movement techniques for a manual task, it is necessary to
observe actual human motions and classify them into distinct groups. Motion capture
technologies facilitate the former and enable construction of large-scale motion databases.
In fact, the MBMS model provides a structure which facilitates consideration of
alternative movement techniques, as for a given input simulation scenario, the root
motion finder can find multiple root motions for modification. This set of root motions
might exhibit variability in movement techniques and by categorizing the root motions
according to movement techniques and modifying individual root motions according to
the input scenario, it is possible to predict motions based on alternative movement
techniques.

Although the MBMS framework facilitates consideration of alternative movement
techniques, it is not clear on what basis root motions should be classified and categorized.
Motions could be visually inspected and subjectively classified, but this approach is
likely to be inaccurate, inconsistent, and time-consuming. The current study presents a
novel quantitative method for representing movement techniques and a classification
approach based on it, and constitutes the ‘movement technique classifier’ component in
the framework of the MBMS. The usefulness of the proposed methods is demonstrated
through analyses of actual human motion data.
6.2 Methods

A set of root motions achieving similar manual tasks are assumed to be given as input data. A motion in the input data set is represented as a set of joint angle-time trajectories:

$$\Theta(t) = [\theta_1(t) \cdots \theta_j(t) \cdots \theta_J(t)]^T$$

where $j$ is an index for the $J$ body joint degrees of freedom ($j = 1, \ldots, J$) and $t$ represents time in $[0,T]$. The goal is to classify the root motions to reveal distinct movement techniques. In doing so, each motion’s underlying movement technique is first quantitatively represented. The idea is that this can be done by quantifying contributions of individual joint rotations to the achievement of the task goal. This idea is consistent with the previous observations that alternative movement techniques, such as the stoop and the squat, differ essentially in the recruitment of the available joint degrees of freedom.

The contribution of the motion of the $i^{th}$ body joint during the movement $\Theta(t)$ can be assessed by comparing $\Theta(t)$ with a hypothetical motion, $\Theta'(t)$, which is identical to $\Theta(t)$ but ridden of the motion of the $i^{th}$ body joint degrees of freedom. In other words, in $\Theta'(t)$,

$$\Theta'_j(t) = \theta_j(t) \text{ if } j \neq i \text{ and } \Theta'_j(t) = \theta_j(0) \text{ if } j = i \text{ for all } t.$$  

If the difference between $\Theta(t)$ and $\Theta'(t)$ is large, then the effect of the motion of the $i^{th}$ body joint degree of freedom to the movement $\Theta(t)$ can be regarded as large. Since the trajectory of the end-effector (normally the human hand) in the task space is directly related to the achievement of the task goals, that is, target acquisition, $\Theta(t)$ and $\Theta'(t)$ are compared in the end-effector trajectory domain and the contribution of the $i^{th}$ body joint motion is defined in the task space as follows:
\[
CX' = \frac{1}{T} \int (x(t) - x'(t)) \, dt
\]  
(2) \[
CY' = \frac{1}{T} \int (y(t) - y'(t)) \, dt
\]  
(3) \[
CZ' = \frac{1}{T} \int (z(t) - z'(t)) \, dt
\]  
(4)

where \([x(t) \ y(t) \ z(t)]^T\) and \([x'(t) \ y'(t) \ z'(t)]^T\) denote the end-effector trajectories in the task space corresponding to \(\theta(t)\) and \(\theta'(t)\), respectively. \(CX', CY',\) and \(CZ'\) can be negative or non-negative depending on the direction of the effect of the joint movement on the end-effector trajectory.

The above quantification allows comparisons of effects of different body joint rotations on a single scale, as \(CX', CY',\) and \(CZ'\) express the contributions of different angular rotations in terms of the end-effector movement. \(CX', CY',\) and \(CZ'\) are further normalized to be represented on a relative proportional scale defined between \([-100,100]\):

\[
PCX' = 100 \frac{CX'}{\sum_{j=1}^{100} |CX'|}
\]  
(5) \[
PCY' = 100 \frac{CY'}{\sum_{j=1}^{100} |CY'|}
\]  
(6) \[
PCZ' = 100 \frac{CZ'}{\sum_{j=1}^{100} |CZ'|}
\]  
(7)

Three J-element vectors, \(JCVX = [PCX' \ldots PCX']\), \(JCVY = [PCY' \ldots PCY']\), and \(JCVZ = [PCZ' \ldots PCZ']\), characterize a motion’s underlying movement technique along the three orthogonal axes in the task space. A 3J-element vector \(JCV = [JCVX \ JCVY \ JCVZ]\) is used as a collective movement technique index.
Once all the motions in the input data set are represented in terms of \textit{JCV}, statistical clustering methods, such as the K-means clustering technique (Johnson and Wichern, 1998), can be applied on the \textit{JCV} data set to form clusters of \textit{JCV} values by similarity. Each cluster is hypothesized to represent a distinct movement technique.

In order to test if the proposed \textit{JCV} can discern different movement techniques, it was used to characterize the well known stoop and squat lifting techniques (Study 1). Also, to test if the \textit{JCV} can be used to discover alternative movement techniques from unknown movement data, a set of three-dimensional, one-handed whole-body load transfer motions was analyzed (Study 2).

In Study 1, six subjects performed sagittal plane lifting tasks in which they lifted a box to the waist level. Each subject was asked to perform sixteen stoop lifts and sixteen squat lifts: For each technique, combinations of two box weights (20 lbs and 30 lbs), two box sizes (small and large) and two initial box heights (Floor and 6 inches above floor) were considered with two repetitions for each condition. Across all subjects, a total of 96 stoop and 96 squat lifting motions were recorded. The motions were recorded by a McReflex motion capture system at a sampling frequency of 60 Hz. The human body was represented as a five-segment open kinematic chain shown in Figure 1. A lifting motion was represented as five joint angle time trajectories ($J = 5$). The stoop and the squat lifting techniques were characterized and compared in \textit{JCVX} (horizontal direction) and \textit{JCVY} (vertical direction) values.
In Study 2, ten male and ten female subjects participated. The age of subjects ranged from 20 to 70 (average = 43.6 yrs). The stature ranged from 150cm to 191cm (average = 169cm). Subjects performed a whole-body, one-handed load transfer task: Prior to the movement, subjects were holding a cylindrical object placed on a wooden plate in an upright standing posture, and at the tone they initiated the movement transferring the object to a target plate near the floor in front of the body. The target plate was 14 cm, 35 cm, and 17 cm away from the left ball of foot in the X, Y, and Z directions, respectively. Figure 2 shows the initial posture and the location of the target plate. Each subject performed a single trial, and therefore a total of 20 motions were recorded (labeled as Motion 1 ~ Motion 20). Each subject performed a motion in a self-selected manner except that he/she was instructed to maintain the left ball of foot at a constant position throughout the movement; the left ball of foot served as the root location of the linkage system. The right foot was free to move.
Figure 6.2. Initial posture at the start of motions and the location of the target destination.

The human body representation consisted of 17 body segments, which had 38 joint degrees of freedom (Figure 3). Each motion was composed of 38 joint angle trajectories \( (J = 38) \) and was characterized by a 114-element vector \( \mathbf{JCV} \) (the concatenation of \( \mathbf{JCVX} \), \( \mathbf{JCVY} \), and \( \mathbf{JCVZ} \)).

Figure 6.3. Three-dimensional whole-body representation of the human body and joint degrees of freedom.
In order to identify alternative movement techniques, a K-means clustering analysis was conducted on the twenty JCV data. The K-means clustering method partitions items (in our case, JCVs) into a collection of K clusters such that the items within a cluster are closer to one another than they are to the items in different clusters (Johnson and Wichern, 1998). The distance between two JCVs was defined as the Euclidean (L_2) distance. To visualize the distance relationships between JCVs, the multidimensional scaling was adopted to project JCV data points onto a two-dimensional plane through dimension reduction. Since the number of distinct movement techniques associated with the task was not known a priori, the K-means analysis was run for several choices of K, and the K value that maximizes the between-cluster variability relative to the within-cluster variability was chosen (Johnson and Wichern, 1998). In order to test if motion clusters represent distinct movement techniques, motions within and between clusters were visually compared through stick-figure animations.

6.3 Results

6.3.1 Study 1: Characterizing the Stoop and the Squat Lifting Techniques

During the stoop lifts, the hip and the shoulder joint rotations were found to primarily affect the formation of hand motion trajectories in both the horizontal and the vertical directions: The median PCX values associated with the hip and the shoulder joints were 38% and -46%, and the median PCY values, 47% and -26% (Figure 4a and 4b).
During the squat lifts, the ankle, the knee, and the hip joint rotations were found to be the prime movers of the hand: The median PCX values associated with the three joints were -18%, 30%, and 27%, and the median PCY values, 27%, -23%, and 36% (Figure 5a and 5b).

(a) JCVX for stoop lifting motions (96 motions)

(b) JCVY for stoop lifting motions (96 motions)

Figure 6.4. Box plots summarizing JCVX (a) and JCVY (b) for the stoop lifting motions. A stick figure animation of a representative stoop lifting motion is provided.
Figure 6.5. Box plots summarizing JCVX (a) and JCVY (b) for the squat lifting motions. A stick figure animation of a representative squat lifting motion is provided.
6.3.2 Study 2: Classification of Motion Capture Data to Discover Alternative Movement Techniques

The twenty JCVs and their proximity relationships are depicted in Figure 6. Three clusters of motions were found by the K-means clustering analysis. Three alphabetical letters (A, B, and C) in the plot represent the positions of the JCVs in the two-dimensional space, and their membership to the three clusters identified by the K-means analysis. Group A consists of eight motions (Motion 3, 4, 10, 12, 13, 14, 17, and 19). Group B has nine members (Motion 1, 5, 6, 7, 9, 15, 16, 18, and 20). Finally, Group C was formed by three motions (Motion 2, 8, and 11).

![Figure 6.6. Three clusters of motions formed by the K-means analysis (A, B, and C). The proximity relationships are visualized in a multidimensional scaling plot. The numbers shown in the upper left of the alphabetical letters are the movement numbers (1–20).](image)

Figure 7-9 show stick figure animations of motions belonging to each motion cluster (three for each): Five instantaneous postures (at the beginning, 25%, the middle, 75%, and the end of the movement) are provided for each motion. The three motion
clusters were found to represent distinct movement techniques, as motions within each group were visually similar to one another, while motions belonging to different groups appeared fundamentally different; Group A motions (Figure 7) utilized moderate knee flexions, large torso flexions, and little-to-moderate torso lateral bending to the left. Group B motions (Figure 8) also utilized moderate knee flexions and large torso flexions, but they were characterized by significant lateral torso bending to the right. Group C motions (Figure 9) primarily rely on deep knee squatting with possible back stepping of the right foot.

6.4 Discussion

Understanding alternative movement techniques is important in ergonomic task evaluations. The MBMS model structure enables considerations of alternative movement techniques in simulating motions, as it can find multiple root motions for a given input simulation scenario. A quantitative index was developed to represent motions’ underlying movement techniques, and a statistical classification approach was introduced to discover alternative movement techniques from a set of root motions.

Our hypothesis was that 1) the movement technique underlying a motion can be quantitatively described by computing contributions of individual joint rotations to the achievement of the movement task goal (Joint Contribution Vector), and 2) when given a set of motion recordings, by representing them in JCV and applying a statistical clustering method on the JCV data, it is possible to lump them into clusters that represent distinct movement techniques.
Figure 6.7. Three motions belonging to Group A: Motion 10, 12, and 17.
Figure 6.8. Three motions belonging to Group B: Motion 5, 7, and 16.
Figure 6.9. Three motions belonging to Group C: Motion 2, 8, and 11.
The validity of the proposed approach was demonstrated by two movement analyses: In Study 1, the JCV index was found to characterize and discern the stoop and the squat lifting techniques (Figure 6.4 and 6.5). In Study 2, the JCV index in combination with the K-means clustering method was found to be able to discover distinct movement techniques from a set of three-dimensional whole-body motions (Figure 6.6); Visual inspections of the motions confirmed that identified motion groups represent fundamentally different movement patterns (Figure 6.7-6.9). The results support our initial hypothesis.

The proposed JCV index is similar to the dynamic lifting strategy index proposed by Zhang et al. (2000) in that they both quantify the effects of joint rotations to the end-effector movement. However, the two indexes characterize motions in different domains: The JCV index characterizes the entire movement trajectory, while the dynamic lifting strategy index, instantaneous motion changes. It might be useful to investigate whether or not the two indexes are consistent with each other in order to further validate both approaches. Compared to previous movement technique representations, the strength of the proposed JCV index is that it is not specific to certain types of motions (e.g., sagittal-plane lifting motions) but can be used to characterize general three-dimensional whole-body motions. Also, its simple computation, which involves neither iterative searches nor differentiation of forward kinematic equations, makes it attractive for applications that require fast computations or large-scale data processing.

Limitations of the present study are acknowledged: Firstly, the JCV index defines the notion of movement techniques only in terms of joint angle and end-effector trajectories, and does not concern other domains of motion representation: For example,
the joint torque space, the muscle stress space, the neuronal activation space, etc. Although the JCV index was found to be a useful tool for representing and classifying gross whole-body motions, other metrics could be conceived in different domains. Secondly, the use of K-means clustering method (or any other discrete clustering analyses) assumes discontinuity among movement techniques (clusters of motions), which may not hold true in all cases. New statistical modeling approaches may need to be adopted to represent continuous transitions among movement techniques. Thirdly, the present study considered only the hand as the end-effector, and this may not be enough to fully characterize a motion’s underlying movement technique. Especially, since the balance maintenance is an important part of the task goal achievement, it may be necessary to characterize how individual joint rotations affect the body balance maintenance in representing a motion’s underlying movement technique. To do so, the center-of-mass during a motion could be treated as an end-effector, and a new JCV index could be developed accordingly.

The three movement techniques found in Study 2 seem to have biomechanical and physiological trade-offs. Related to this, the identification of alternative movement techniques seems to inevitably lead to a follow-up research question: How is one movement technique chosen over others and why? The selection of movement technique might be related to the interaction between trade-offs in different movement techniques and idiosyncrasies of individual subjects. Testing this hypothesis would further enhance the understanding of human motion planning.
6.5 References


CHAPTER VII

A CASE STUDY: LOW BACK BIOMECHANICAL ANALYSES OF MAIL TRAY HANDLING TASKS IN USPS WORKPLACES

This chapter describes a motion simulation case study that demonstrated the utility of the MBMS approach. In this case study, potential risks of low back injuries associated with a manual handling task in USPS (United States Postal Service) workplaces were identified through the use of motion modification. Also, workplace redesign recommendations were derived from the motion simulation study.

7.1 Mail Tray Handling Tasks in USPS workplaces

In USPS workplaces, workers frequently remove mail trays from the top of a mail processing cart and place them in various locations on a General Purpose Mail Cart (GPMC). A CAD (Computer-aided Design) representation of GPMC with relevant dimensions is shown in Figure 7.1. An illustration of typical tray handling task is provided in Figure 7.2.

Rider et al, (2000) conducted an ergonomic evaluation of the mail tray handling task. In their study, a large man, approximately 95th percentile with respect to stature and weight, removed mail trays from the top of a mail processing cart and placed them in the highest and the lowest possible locations on a General Purpose Mail Cart (GPMC). The motions were recorded using Ascension Technologies’ Wireless Motion Capture
System. Physical characteristics of the subject are provided in Table 1. The subject was experienced in performing mail-handling duties.

![Figure 7.1. General Purpose Mail Cart (GPMC).](image)

![Figure 7.2. A worker removing a tray from the push cart and placing it on the bottom shelf of GPMC.](image)

<table>
<thead>
<tr>
<th>Table 7.1. Physical characteristics of subject</th>
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<tr>
<td>Gender</td>
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Sequential static low back compressive force analyses were conducted based on the motion capture data. The results of the low back analyses suggested that the 95th male subject might be at risk of a low back injury when placing a 25-lb tray to the lowest position in the GPMC, as shown in Figure 7.2.

7.2 Lowback Biomechanical Analyses and Workplace Redesign through Motion Modification

To evaluate risks of low back injuries more comprehensively and further suggest workplace redesign recommendations, additional biomechanical analyses were considered. The objectives of additional analyses were:

- To estimate the lowest acceptable height for a shelf that a male of 95th percentile stature can place a tray without significant risk of a low back injury.
- To estimate the tallest stature of a male that can place a tray on the bottom shelf of the current GPMC without significant risk of a low back injury.

A “significant risk” is deemed present when the lower back compression force exceeds the NIOSH Action Limit of 3400 Newtons (N).

To achieve the above objectives, low back biomechanical analyses based on additional motion data corresponding to alternative shelf heights and different subject statures were necessary. Additional motion capture experiments can provide necessary motion data. However, since motion capture is costly and time consuming, motion simulation based on motion modification was adopted as an alternative approach in this study. In this motion modification approach, the single movement towards the bottom shelf, recorded in the initial ergonomic evaluation study by Rider et al. (2000), served as
the root motion for the MBMS, and motions corresponding to alternative shelf heights and stature levels were simulated by modifying this root motion. EDS PLM Solutions’ Jack was used for visualization and analysis purposes.

7.2.1. Motion Simulation for Modified Destinations

To determine the range of acceptable shelf heights for the tall man to place a tray, the root motion was modified to simulate motions for varying end-point heights (i.e., varying shelf heights). The end-point height was adjusted vertically in 10 cm increments, from -30 to +30 cm of the original value, as shown in Figure 7.3.

Figure 7.3. Depiction of vertical adjustments made to end-point destination of task.

Jack’s Lower Back Analysis tool was used to compute time trajectories of low back disc compressive force corresponding to the simulated motions. The computed disc compressive force time trajectories were examined to determine the range of shelf heights.
that does not create low back disc compressive forces higher than the NIOSH Action Limit (3400N).

7.2.2 Motion Simulation for Modified Anthropometry

In order to determine the range of worker stature for which the tray handling task would not create excessive disc compressive forces, the root motion was modified to simulate motions for different body sizes. Seven digital humans were created for this analysis: one that represented the actual subject and six that ranged from 70% to 130% of the subject’s stature and weight in 10% increments. Figure 7.4 shows the differently sized digital humans.

Similarly to the previous analysis, time trajectories of low back compression force are computed for the simulated motions. The computed disc compressive force trajectories were examined to determine the range of stature for which disc compressive forces would not exceed the NIOSH Action Limit.

Figure 7.4. Differently sized digital humans
7.3 Results

7.3.1 Motion Simulation for Modified Destinations

Figure 7.5 graphically illustrates the motion modifications performed for modified destinations. The final postures of the root motion and the six simulated motions for varying shelf heights are provided as superimposed images (Note that final hand locations are different).

Figure 7.5. Example of digital humans of identical stature lowering a mail tub to vertically adjusted end-points.

Time trajectories of low back disc compressive force for the root motion and the six simulated motions for alternative shelf heights are depicted in Figure 7.6. The maximum low back disc compressive force in the root motion was found to be approximately 3,800 N, which exceeds the Action Limit by 400 N. Figure 7.6 also shows that the subject can safely place a 25-lb tray when the shelf is raised 20 cm or more from the original location.
Figure 7.6. Time trajectories of low back compression force associated with seven different shelf heights.

7.3.2 Motion Simulation for Modified Anthropometry

Figure 7.7. graphically illustrates the motion modifications performed for changes in anthropometry. The final postures of the root motion and the six simulated motions for differently sized digital humans are presented as superimposed images. Note that the final hand locations are identical despite the differences in human size.

Figure 7.7. Example of digital humans with varying stature lowering a mail tub to the same destination.
Time trajectories of low back disc compressive force for the root motion and the six simulated motions for different human statues are depicted in Figure 7.8. Figure 7.7 shows that a person who is 177 cm tall or less place a 25-lb tray on the bottom shelf of the current GPMC without being subjected to disc compressive forces exceeding the NIOSH Action Limit.

Figure 5.8. Time trajectories of low back compression forces for workers of seven different statures.

7.4 Discussion

A real human motion from a motion capture experiment was modified to create motions for alternative task scenarios – different workstation heights and subject statures. The motions generated by the motion modification algorithm exhibited smooth movement patterns, as the modified motions preserve the naturalness of the existing motion data. This observation is consistent with the findings from the MBMS prediction accuracy analyses presented in Chapter 5.

The time trajectories of low back disc compressive forces corresponding to the motions generated for different scenarios (in Figure 7.6 and 7.8) exhibits similarities between the root motion and the simulated motions in general movement pattern. This
shows that the motion modification algorithm preserved general characteristics of the root motion in deriving the simulated motions, not only in the joint-angle-time domain but also in the kinetics domain.

The proposed approach of combining motion capture data and MBMS was shown to answer important ‘what-if’ questions essential in ergonomic task evaluation and redesign (Figure 7.6 and 7.8). Figure 7.6 provides a range of destination heights that would not impose serious biomechanical stresses on the subject’s lower back. Figure 7.8 shows the effect of human stature on low back biomechanical stress during the task. These results confirmed the initial report from the USPS that a tall-person might be subjected to low-back injury risk during the mail tray handling task (Rider et al., 2000).

The combination of motion capture and MBMS has a significant advantage over the conventional motion capture experiment, as it saves the time and effort. In addition, it may also complement existing human motion simulation models that predict typical, stereotyped motions such as reach and lifting (Hsiang and Ayoub, 1994; Zhang et al., 1998; Faraway, 1997). When a task and its workplace are very unique and motions occurring in that particular task are not ‘stereotyped,’ the existing motion simulation models may not be applicable. In such cases, a quick motion capture experiment and motion modification would enable designers to consider human motions in alternative designs with minimal effort and time requirements, as shown in the current case study. Although the MBMS approach normally assumes existence of a large scale motion database (Chapter 3), it is useful when only a small set of motion data is available. Also, an MBMS system can always increase its movement repertoire with simple additions of new motion capture data.
7.5 References


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1042.

261.
CHAPTER VIII
CONCLUSIONS AND FUTURE RESEARCH

8.1 Research Contributions

The research presented in this dissertation was conducted to 1) propose a novel motion simulation model structure that reproduces the qualities of the actual human motor system and overcomes the limitations of the existing human motion simulation models (generality, accommodation of multiple movement techniques, and expandability), 2) develop a novel motion simulation algorithm that predicts human motions accurately in a wide variety of situations and, and 3) to experimentally confirm the soundness of the proposed motion simulation model. The specific contributions include:

- Development of the Memory-based Motion Simulation (MBMS) model structure;
- Development of MBMS components – motion database, root motion finder, movement technique classifier, and motion modification algorithm;
- Experimental evaluation of the motion prediction accuracy of the MBMS, and
- Demonstration of the usefulness of the movement technique classifier through actual motion data analyses.

The following sections present specific conclusions obtained from the investigation, and identify future research problems regarding human motion simulation and digital human technology.
8.2 Research Conclusions

8.2.1. Advantages of Memory-based Motion Simulation Model Structure

The unique structure of the MBMS system allows simulating different types of motions on a single, unified framework, as its memory provides a storage space in which any kind of human motion data can be stored, and the minimum dissimilarity principle embedded in the motion modification algorithm does not assume any specificity. The experimental validation studies showed that identical MBMS systems were able to accurately predict both seated reach motions and whole-body load transfer motions, which are qualitatively different motions (Chapter 5). The generality of the MBMS system is a major advantage over existing motion simulation models, because the MBMS system requires no additional modeling effort to extend its capability.

The MBMS structure also provides a solution to the alternative movement technique problems, as its memory provides a storage space in which motions based on different movement techniques can coexist. The proposed movement technique classifier allows the MBMS system to recognize the existence of alternative movement techniques in simulating motions for an input scenario (Chapter 6). The MBMS system is distinguished from the existing motion simulation models, as it has a means of dealing with variability in human motions, at the level of movement technique.

Finally, the MBMS system can continually learn new motor skills due to the existence of its memory. Other than conducting motion capture experiments and storing the obtained data in the memory, no additional modeling effort is required to train the system to learn new motor skills.
8.2.2 Motion Modification Algorithm

The motion modification algorithm (Chapter 4) generalizes and adapts existing motion data: Given a root motion, the algorithm analyzes the root motion and segments its joint angle-time trajectories to identify its fundamental spatio-temporal movement structure. The identified motion structure leads to a parametric representation of possible variants of the root motion (Generalization). Once a root motion is generalized, the algorithm can adapt the root motion to novel input simulation scenarios by changing the parameter values. Using the minimum dissimilarity principle, among all possible variants of the root motion, the algorithm finds the motion that resembles the root motion the most and satisfies the novel input simulation scenario.

Two experimental validation studies were conducted to evaluate the prediction accuracy of the motion modification algorithm (Chapter 5).

Seated reach motion prediction study (Section 5.1)

A set of one-handed seated reach motions were modified to predict motions for novel target locations. The modified (predicted) motions were compared with real human motions. The conclusions drawn from the study were as follows: The close similarities between the joint angle trajectories of the root and modified motions and the preservation of the bell-shaped velocity profile of the end-effector show that the modification process conserves the characteristics of the overall pattern of the root motion.

The statistical analysis confirms the prediction accuracy of the algorithm. The difference between the natural variability in repeated motions of an individual and the
mean prediction error resulting from 30 cm modifications was at the most 1.3 cm. Despite a statistical significance, this difference is rather small when considering the large distance (30 cm) between the original and new destination target. This difference is negligible (≤ 0.2 cm) when the new destination target is located 15 cm away from the original target.

These results demonstrate the robustness of the algorithm and support its capability to predict motions with an accuracy almost identical to the observed variability in repeated human motions.

Prediction of Whole-body Load Transfer Motions (Section 5.2)

Whole-body one-handed load transfer motions were simulated by a MBMS system, and simulated motions were compared with real human motions in a cross-validation scheme. As in the seated reach prediction study, the prediction error (difference between predicted and real motions) was found to be close to the natural variability of human motions. This suggests that the motion modification algorithm is able to predict three-dimensional whole-body motions accurately.

8.2.3 Movement Technique Classification

A quantitative index termed Joint Contribution Vector (JCV) was developed to represent motions’ underlying movement techniques, and a statistical classification approach was introduced to discover alternative movement techniques from a set of root motions.
The validity of the proposed approach was demonstrated by two movement analyses: In Study 1, the JCV index was found to characterize and discern the stoop and the squat lifting techniques (Figure 6.4 and 6.5). In Study 2, the JCV index in combination with the K-means clustering method was found to be able to discover distinct movement techniques from a set of three-dimensional whole-body motions (Figure 6.6); Visual inspections of the motions confirmed that identified motion groups represent fundamentally different movement patterns (Figure 6.7-6.9). The results support our initial hypothesis.

8.2.4 Relation to Studies on Human Movement Planning

The most important characteristics of the MBMS approach is that it is compatible with the GMP theory (Section 2.1). In fact, the proposed MBMS system is in support of the GMP theory, as it demonstrated that it is possible to implement a computer program that plans movements based on the GMP theory.

The proposed motion modification approach tends to agree with the hypothesis that multijoint reach movements can be planned in the intrinsic joint angle space without superceding hand trajectory planning in the extrinsic Cartesian space (Atkenson and Hollerbach, 1985; Hollerbach, 1990; Prablanc and Martin, 1992; Osu et al., 1997). Indeed, modification of “stored” joint angle trajectories was sufficient to produce motions that exhibit “invariants,” such as the bell-shaped velocity profile of the end-effector (Morasso, 1981; Soechting and Lacquaniti, 1981; Abend et al., 1982) and, by construction, maintained the covariation of joint motions (Lacquaniti et al., 1986) and cascaded scaling of joints time profiles (Hollerbach, 1990) that have been associated with
planning in the extrinsic space. Nevertheless, as this approach still requires to solve the inverse kinematics problem posed by the determination of the terminal postures necessary to implement a new motion scenario, it cannot be excluded that hand space planning occurs also.

The dual planning in intrinsic and extrinsic coordinate systems, suggested by other studies (Haggard et al., 1995; Desmurget et al., 1997), may be a necessity to resolve the indeterminacy associated with the large degrees of freedom and the differences between motion trajectories and the ending posture (Rosenbaum et al., 1995; Rosenbaum et al., 2001). To reduce the degrees of freedom, minimization of jerk (Hogan, 1984; Flash and Hogan, 1985), torque change (Uno et al., 1989), muscular energy (Alexander, 1997), work (Soechting et al., 1995), variance (Harris and Wolpert, 1998), or maximum smoothness (Flash and Hogan, 1985; Uno et al., 1989; Kawato, 1992) have been proposed; however, the optimization of a cost function may not be a priority in movement planning. A simple example is given by the realization that some people select between a squat or a stoop posture to initiate the lift of an object from the ground for a variety of reasons which are not deterministic. In addition, external constraints, such as obstacle on the movement path, or the final posture required by the placement of an object can limit “optimality” in work, energy, etc. Hence, the reduction of degrees of freedom may require different procedures at the beginning, during, and at the end of a motion, and it may be considered that a motion is a link between two postures, as suggested by (Rosenbaum et al., 1995). According to this theory, the CNS simplifies motion planning by retrieving ‘stored’ postures to plan terminal postures and then specifies the motion between the stored postures. When dealing with a complex motion,
the terminal postures can be generalized to multiple ‘via’ postures. Via postures could be used to plan motions for avoiding obstacles in the space (Rosenbaum et al., 1999; Park et al., 2001).

The motion modification process consists of two steps: first, the planning of initial and final postures from the task goal, and second, the planning of motion between these postures. This approach does not optimize performance measures but rather generalizes stored ‘motor’ programs. It is worth noting that the minimum dissimilarity measures shown in (5) and (13) are not a physiological or biomechanical performance criterion. The motion modification concept is not necessarily in conflict with optimal control modeling, as optimization of a performance is not in opposition to the modification of a stored motor program. An example of combination of these two types of computation is given by the Jordan’s neural network model (Jordan, 1990) which was trained to predict smooth arm motions by an optimization principle.

8.3 Limitations of the Dissertation Research and Future Research Problems

In this section, limitations of the current dissertation research are described, and future research problems are suggested.

8.3.1 Models on Motion and Posture Computation

While the current research proposed a model structure and a principle for planning motion trajectories, namely, the minimum dissimilarity principle, it does not provide a clear idea about how computations occur in the actual human system: The motion modification algorithm utilizes a modified steepest descent search algorithm to solve the
inverse kinematics problem. Such an optimization method is useful in implementing the minimum dissimilarity principle in the inverse kinematics solution process, but there is no evidence that the actual human system adopts a gradient based search in solving the inverse kinematics problem. In fact, given the fact that people are extremely good at solving a wide variety of inverse kinematic problems reliably and quickly, a gradient search method is probably not what people utilize. As the digital human research aims to create humanlike virtual human models, models of the computational mechanism for movement planning seems worthy of investigating.

8.3.2 Online Motion Correction

The motion modification algorithm essentially plans only target or ‘nominal’ motion trajectories – kinematic motion trajectories that the neuromusculoskeletal system must follow during the execution of the motion plan. The motion modification algorithm is limited as it does not allow online corrections of movements to compensate for unexpected changes in the environment or disturbances. Online motion correction, however, seems necessary in simulating human motions. Especially, in many real world situations, such as driving a vehicle on irregular terrains or manual tasks that involve moving objects, the human responses to unexpected changes during movement executions may be important in ergonomic evaluations.

8.3.3 Balance and Strength Constraints

The motion modification algorithm does not ensure the satisfaction of body balance and joint strength limit constraints while modifying motions, although it is able to
represent joint range of motion limitations. The algorithm needs to be improved so as to accommodate these constraints and thus prevent unrealistic motions from being generated. Implementing the balance constraints might require an understanding of how a human achieves this secondary goal, which would be beyond solving the mathematical constraint satisfaction. It might be important to understand whether the balance maintenance during a motion is achieved through online feedback control or by preplanning.

8.3.4 Computational Speed

One potential limitation of the motion modification algorithm is its near real-time computational speed with current CPU’s. The algorithm may take up to several seconds because the gradient search algorithm used to modify initial and final postures (Section 4.3.2) often converges to solution slowly. Also, like all iterative search algorithms, the gradient search method may fail to converge to a solution in certain cases despite its low probability. A possible solution to this problem is performing pre-computation. Given an initial set of root motions, it is possible to grow the root motion set by systematically modifying the root motions to generate variants and storing corresponding modified motions back into the motion set. In this fashion, the root motion set (or motion database) will become denser with pseudo-root-motions. With a denser motion database, motion simulation for novel scenarios can be conducted faster, because root motions selected for novel scenarios will be closer to the novel scenarios, and therefore, subsequent motion modifications require only minor changes in the motion modification process.
8.3.5 Motion Database Management

In the MBMS system, the quality of motion simulation is dependent on the content of the memory (the motion database). One would suppose that the more motion data the motion database contains, the better the MBMS system would become. However, an excessively large motion database could have problems, such as the requirement for a large storage place and potentially increased search time for root motion selection. Also, without a good sampling strategy, adding motion data might not enhance the prediction capability of an MBMS system. Two important research questions are:

- How to minimize the size of a motion database by eliminating redundant data?
- How to determine the necessary motion samples by examining the content of the current motion database?

8.3.6 Movement Technique Classifier

Limitations of the movement technique classifier are acknowledged: Firstly, the JCV index defines the notion of movement techniques only in terms of joint angle and end-effector trajectories, and does not concern other domains of motion representation: For example, the joint torque space, the muscle stress space, the neuronal activation space, etc. Although the JCV index was found to be a useful tool for representing and classifying gross whole-body motions, other metrics could be conceived in different domains. Secondly, the use of the K-means clustering method (or any other discrete clustering analyses) assumes discontinuity among movement techniques (clusters of motions), which may not hold true in all cases. New statistical modeling approaches may need to be adopted to represent continuous transitions among movement techniques.
Thirdly, the present study (Chapter 6) considered only the hand as the end-effector, and this may not be enough to fully characterize a motion’s underlying movement technique. Especially, since balance maintenance is an important part of the task goal achievement, it may be necessary to characterize how individual joint rotations affect the body balance maintenance in representing a motion’s underlying movement technique. To do so, the center-of-mass during a motion could be treated as an end-effector, and a new JCV index could be developed accordingly.

8.3.7 Obstacle Avoidance

Interference between physical objects in the workspace and the moving human body may cause serious problems, including errors in manual operation, physical damage and trauma from collision, and increased biomechanical stresses due to movement reorganization for avoiding the obstacles. Therefore, a computer algorithm to detect possible collisions and simulate human motions to avoid obstacles will be an important tool for computer-aided ergonomics and optimization of system design in the early stages of a design process. It seems promising that modifying motions could generate realistic motions that avoid collisions with objects in the workspace (Park et al., 2001). Further developments in this direction would enhance the capability of the current digital human models substantially.

8.3.8 Representation of a Complex, Long Sequence of Motor Behaviors

The MBMS model structure provides a basis for combining different types of motor activities to represent a long sequence of complicated motor behaviors, as it is capable of
simulating motions of different types on a single, unified framework. However, fundamental research questions need to be answered:

- How to select and designate ‘primitive’ motions?
- How to blend two motion data? How to decide whether two motions are blendable?
- How to generate the ‘transitional’ motion to combine two independent motions when two motions are not blendable?

### 8.4 References


Symbolic Structure Representation of Human Motions

Raw motion data are normally represented as time-series. The structure of a time-series is revealed when segmentation of the time-series is performed to meet the following conditions:

- Each segment represents monotonically increasing, monotonically decreasing, or stationary time trajectory, and
- The number of segments is at minimum.

The term ‘structure’ of a time-series refers to segments determined according to the above conditions, their shape (monotonically increasing, decreasing, or stationary over time), and their arrangement in time. A human motion is normally described as multi-dimensional time-series, as there are multiple degrees of freedom varying over time (e.g. a number of joint angle trajectories, a number of joint center location trajectories, etc.).

In the present study, we describe human motions as multiple joint angle trajectories. The structure of a human motion then can be defined as a collection of the structures of individual joint angle trajectories.

Given the above definitions of structure, we propose to use symbols to designate the structure of human motions. The logic is:
To divide a time-series into segments according to the definition (given above) of structure, and

To assign a symbol ('U': up, 'D': down, or 'S': stationary) to each segment of the time-series to describe its shape.

When a kinematic/kinetic motion trajectory is indexed as a string, each symbol in a string would correspond to a meaningful unit of motor activity. For example, a string "UDUD" representing the structure of an elbow joint angle trajectory means a sequence of primitive elbow joint motions "flexion-extension-flexion-extension." Also, a string of symbols can be regarded as an abstraction of the overall shape of a time-series, which is presented in a parsimonious and understandable manner. An example is provided to illustrate how a time-series is converted to its symbolic string representation: A volunteer was asked to describe the structure of an actual angle trajectory shown in Figure A1(a) (a left elbow flexion/extension angle trajectory during a sequence of complex 3-D motions) using the symbolic coding scheme. The results are the letters added to the angle curve shown in Figure A1(a): The structure of the time-series was represented as a string of symbols 'SDSDUSU.'
Figure A1. Symbolic structure encoding algorithm. (a) Symbolic encoding of the example angle trajectory performed by simple visual inspection of the raw trajectory. (b) Detected landmarks (marked with circles) from algorithm with 1 deg/min threshold. (c) Detected major segment boundaries (Marked with squares) are shown based on a 6 Hz cut-off criterion. (d) Assignment of symbols to segments after determining major changes in trajectory values. (e) The final output string after eliminating redundancies in sequential series of symbols (i.e., SDDSDUSU → SDSDUSU).
A Computer Algorithm for Symbolically Encoding Joint Angle Time Trajectories

In order for the symbolic structure coding scheme to be useful in dealing with voluminous motion data, the segmenting and coding tasks must be automated. Implementing such a computer algorithm, however, required consideration of the following issues: 1) experimentally collected time-series always contain ambiguities due to random noise which hinder the determination of segment boundaries, and 2) symbol assignment to resulting segments can be ambiguous as it is not clear how to determine whether a segment represents a significant motion ('U' or 'D') or a stationary state ('S').

The following is the detailed description of the algorithm we developed. The example time-series provided previously in Figure A1(a) will be used to illustrate how the algorithm works.

Find landmarks in the time-series (Step 1)

It is assumed that a uni-dimensional time-series \( x_t \) \((t = 1, \ldots, T)\) is given as the input data for the algorithm. Any appropriate filtering or smoothing operation can be applied to the time-series beforehand.

The algorithm begins by detecting all data points in the time-series which may be used to form segments. Let us call these data points landmarks. Note that landmarks are only candidates for segment boundaries in the subsequent segmentation procedure.

In order for a data point in the time-series to be a possible segment boundary (landmark), one of the six types of transitions should occur at the data point: 'U' to 'D', 'U' to 'S', 'D' to 'U', 'D' to 'S', 'S' to 'U', and 'S' to 'D'. 'U' to 'D' and 'D' to 'U' transitions occur at the extremes of the time-series \( x_t \). Therefore, initially all the extremes are classified as
landmarks by the algorithm. At each time $t$, whether or not the data point $x_t$ is an extreme can be tested by multiplying the leftward slope by the rightward slope:

$$(x_t - x_{t+1}) \times (x_{t+1} - x_t).$$

A negative sign indicates that $x_t$ is an extreme. Transitions involving 'S' can be detected again by checking the leftward and the rightward slopes. If and only if one of the two slopes is zero or its absolute value is small enough (less than a user specified threshold $\varepsilon_{slope}$) to be considered as a possible start or end of a stationary segment, $x_t$ is classified as a landmark by the algorithm. $\varepsilon_{slope}$ was set at 1deg/min in dealing with joint angle trajectories. A logic describing the landmark detection procedure is as follows:

$$l_1 = 1$$

$$i = 2$$

FOR $iter = 2$ TO ($T-1$)

IF $$((x_{iter} - x_{iter-1}) \times (x_{iter+1} - x_{iter}) < 0) \text{ OR } (|x_{iter} - x_{iter-1}| \leq \varepsilon_{slope}) \text{ AND } (|x_{iter+1} - x_{iter}| \geq \varepsilon_{slope}) \text{ OR } (|x_{iter+1} - x_{iter}| \leq \varepsilon_{slope}) \text{ AND } (|x_{iter} - x_{iter-1}| \geq \varepsilon_{slope})$$

THEN

$$l_t = iter$$

$$i = i + 1$$

ENDIF
The procedure outputs the occurrence times of landmarks. The landmark detection algorithm was applied to the example time-series with the threshold value of 1 deg/min. The result is shown in Figure A1(b). Landmarks in the example time-series were marked with circles.

**Segment boundary selection (Step 2)**

Once landmarks are identified, the algorithm proceeds to divide the time-series into segments. Each landmark is a potential segment boundary at which a segment begins or ends. However, not all of the landmarks might be segment boundaries in the presence of transient, insignificant fluctuations, noises, or ambiguities. This becomes clear when examining Figure A1(b): There are dense clusters of landmarks in plateaus, which are seemingly due to random noise in the time-series. Demarcating segments using all these densely clustered landmarks would produce too many segments, which may only represent insignificant transient fluctuations that would not represent the major structure of the motion.

In order to select major segment boundaries, we propose to examine whether or not each landmark meets the following conditions:
o The landmark is located farther than a predetermined threshold $\varepsilon_{\text{time}}$ from at least one of the adjacent landmarks in the time axis.

o The landmark is located farther than a predetermined threshold $\varepsilon_{\text{time}}$ from the nearest segment boundary (which has been found up to that point) in the time axis.

The first condition ensures that the landmark adjoins at least one segment. The second condition ensures that no two segment boundaries are too close to each other in time. If a landmark satisfies the above conditions, it is determined as a segment boundary. The first and the last data point of a time-series are segment boundaries by definition. $\varepsilon_{\text{time}}$ be set at 1/6 sec for discrete goal oriented movements such as reach or lifting, since 6 Hz is a widely used cut-off frequency for analyzing various forms of natural human movement data. A logic describing the segment boundary selection procedure is as follows:

\[
B = [l]
\]

FOR $iter = 2$ TO $(l-1)$

\[
p = l_{iter} - l_{iter-1}
\]
\[
q = l_{iter+1} - l_{iter}
\]
\[
u = l_{iter} - b_{end}
\]
The procedure outputs the occurrence times of segment boundaries. The segmentation algorithm was applied to the preceding example time-series. The result is shown in Figure A1(c). Major segment boundaries are marked with squares.
Assign a symbol to each segment to describe its shape (Step 3):

After the time-series is divided into major segments, the algorithm will assign symbols to segments to describe their shape. A symbol among three ('U', 'D', and 'S') will be chosen and given to each segment, according to the displacement of the time-series during each segment: If the displacement is greater than or equal to a user-defined threshold $\varepsilon_{\Delta t}^U$, the symbol 'U' is assigned to the segment. If the displacement is less than or equal to $\varepsilon_{\Delta t}^D$, the symbol 'D' is assigned to the segment. Finally, the symbol 'S' will be given, if the displacement value is less than $\varepsilon_{\Delta t}^U$ and greater than $\varepsilon_{\Delta t}^D$. $\varepsilon_{\Delta t}^U$ and $\varepsilon_{\Delta t}^D$ are set as 0.3–0.7 degrees. A logic description of the symbol assignment procedure is as follows:

$$
C = [ ]
$$

FOR \text{ \textit{iter}} = 1 \text{ TO } J

$$
\Delta x = x_{b_{\text{\textit{iter}}}} - x_{b_{\text{\textit{iter-1}}}}
$$

IF $(\Delta x \geq \varepsilon_{\Delta t}^U)$ THEN

ADD(C, 'U')

ELSEIF $(\Delta x \leq \varepsilon_{\Delta t}^D)$ THEN

126
ADD(c, 'D')
ELSE
THEN
ADD(c, 'S')
ENDIF
ENDFOR

The procedure is applied to our previous example time-series resulting in a string of symbols 'SDDSDUDU' as shown in Figure A1(d).

Eliminate possible redundancies in the symbolic representation (Step 4):

The symbolic representation produced from Step1, 2 and 3 may contain redundancies, i.e., consecutive segments with identical symbols: For example, our example time-series was described as 'SDDSDUSU' which can be further simplified as 'SDSDUSU.' Possible redundancies are eliminated in the segmentation by merging consecutive segments with identical symbols. The procedure is applied to our example time-series resulting in a string of symbols 'SDSDUSU', as shown in Figure A1(e). A logic description of the redundancy elimination procedure is as follows:

\[
\mathbf{B}^* = [b_1] \\
\mathbf{C}^* = [c_1]
\]
FOR iter = 2 TO J

IF $c_{iter} \neq c_{end}$

THEN

ADD($B^*, b_{iter}$)

ADD($C^*, c_{iter}$)

ENDIF

ENDFOR

ADD($B^*, T$)

OUTPUT $B^*$ AND $C^*$
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BIBLIOGRAPHY


