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STUDY OF BI-CRITERION UPPER BODY POSTURE PREDICTION USING PARETO OPTIMAL SETS

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ABSTRACT

This study involves further development of a direct approach to optimization-based posture prediction by using multi-objective optimization (MOO). Human performance measures representing joint displacement and delta potential energy are aggregated to predict more realistically, how virtual humans move. It is found that potential energy does not govern independently human posture. Rather, it must be coupled with another objective to avoid non-unique solutions and to improve realism. In any case, it is more suitable when reaching behind the avatar. Thus, we refine the idea of task-based posture prediction, concluding that performance measures should depend not only on the task being completed but also on where the task is completed relative to the human. Pareto optimal sets are depicted using the weighted sum and weighted min-max methods for MOO. By leveraging a special form of Pareto optimal set, insight is gained concerning how the functions should be combined. We find that the two MOO methods perform equally well, and the general form of the sets is independent of the target (to be touched with the finger) location.

KEY WORDS

Posture prediction, Pareto optimal, multi-objective, optimization

1. INTRODUCTION

A fundamental component of virtual humans, which are used to test and improve design prototypes more cost effectively, is the ability to predict postures. The basic posture prediction problem entails having an avatar contact a specified target point with the *end-effector*, using a realistic and natural posture, where an end-effector is a point of interest on a kinematic system such as an arm. Although a few approaches for solving the posture prediction problem are presented in the literature, the direct optimization-based approach [1,2,3,4,5] provides distinct advantages. It affords the virtual human a substantial amount of autonomy; it is applicable to models with a relatively high number of degrees-of-freedom (DOF); and it can yield real-time predictions. We capitalize on these advantages to provide new understanding of human postures and to develop new capabilities. With the direct optimization-based approach, the joint angles for all DOFs in the human model provide the design variables and are determined by optimizing a *human performance measure* such as joint displacement or energy. In general, performance measures are metrics that govern how a virtual human moves, given a particular scenario. The position of the end-effector is constrained to remain on a specified point, line, or plain, and the joint angles are constrained to remain within specified limits. The prediction of a single posture requires the solution of only one optimization problem.

A key hypothesis behind this approach is that human motion is characterized by the performance measures, and which measure is most applicable depends on the nature of the task being completed. This hypothesis is extended to suggest that posture can be governed by multiple measures simultaneously. Then, one must aggregate the performance measures using multi-objective optimization (MOO). Consequently, we present a novel study of multi-objective optimization within the context of posture prediction.

Although human posture prediction has been studied extensively, methods and concepts associated with MOO have not yet been exploited fully. In fact, when incorporating multiple performance measures simultaneously, only the weighted sum method has been used with ad hoc weights, and analysis of the results in terms of MOO is not provided. Furthermore, the weighted sum method has only been used to yield a single solution point. Evaluating sets of solution points, studying additional methods, and determining which combination of performance measures predicts postures most effectively, can improve the predictive model and increase understanding of how and why humans assume particular postures. Use of different MOO methods in this capacity can also provide a practical comparison of the methods. Ref. 6 provides an initial feasibility study for MOO-based posture prediction, and this paper presents a more in depth look at the topic.

There are essentially two fundamental approaches to posture prediction. First, one can predict posture based on prerecorded motion, anthropometric data, and functional regression models [7,8,9,10]. Alternatively, one can use inverse kinematics to predict posture, without observed data. There is a variety of approaches to inverse kinematics, one of the most common of which is the pseudo-inverse method [11,12,13]. The solution (set of joint angles representing a posture) is determined iteratively using the pseudo-inverse of the Jacobian matrix, which represents the derivatives of the end-effector position with respect to the joint angles. An independent optimization problem is solved with each iteration in order to minimize the deviation of the resolved posture from a predetermined reference posture. Some authors combine the two above-mentioned approaches [14,15]. The direct optimization approach falls under the category of inverse kinematics and requires no preliminary posture data.

In this paper, first, an overview is provided of the optimization formulation for posture prediction. Then, a new hybrid method (combination of genetic algorithm and gradient-based algorithm) is developed and used for function-normalization. Two performance measures, joint displacement and a modified form of potential energy, are compared. Pareto optimal sets for four different targets, which are determined using the weighted sum method and the weighted min-max method, are also presented and discussed. By depicting the Pareto optimal sets, we evaluate the relationship between the two performance measures, and we determine how dependent the results are on the nature of the target. Concurrently, the relative performance of the weighted sum method and the weighted min-max method is analyzed in terms of the methods' ability to depict the Pareto optimal set.

2. OPTIMIZATION-BASED POSTURE PREDICTION

Essentially, the body is modeled as a kinematic system, a series of links connected by revolute joints that represent musculoskeletal joints. It incorporates the spine, the shoulder, and the arm. A generalized coordinate, q_i, represents the rotational displacement of each joint. Thus, $\mathbf{q} \in \mathbf{R}^n$ is the vector of n-generalized coordinates in an n-DOF model and represents a specific posture, where $\mathbf{q} = \begin{bmatrix} q_1 & q_2 & \cdots & q_n \end{bmatrix}^T$. With this study, a 21-DOF model for the human torso and right arm is used, as shown in Figure 1, where each cylinder represents one DOF.

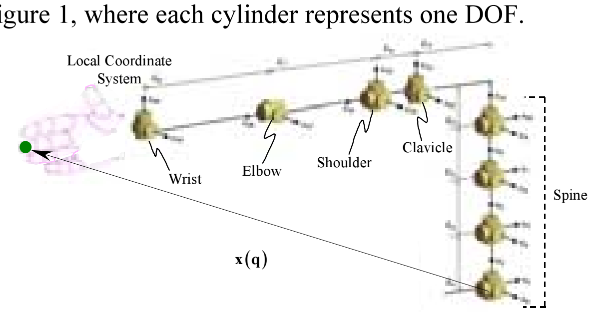

Figure 1: Detailed 21-DOF model

The optimum posture (set of q-values) is determined by solving the following optimization problem:

Find: $\mathbf{q} \in R^n$ (1)

to minimize: *Joint Displacement*, *Delta Potential Energy*

subject to: $\left[\mathbf{x}(\mathbf{q}) - \mathbf{x}^P \right]^2 \le \varepsilon$

$$q_i^L \le q_i \le q_i^U;\ i = 1, 2, \ldots, n$$

where $\mathbf{x}(\mathbf{q}) \in R^3$ is the position vector in Cartesian space that describes the location of the end-effector as a function of the generalized coordinates and in terms of the global coordinate system located a the base of the spine. Given a set of generalized coordinates, the position of the end-effector is calculated using the DH-method [16]. $\mathbf{x}^P$ is the target position. The design variables are the generalized coordinates q_i. The first constraint in (1) requires that the end-effector contact a predetermined target in Cartesian space, where ε is a small positive number that approximates zero. In addition, each generalized coordinate is constrained to lie between lower and upper limits, represented by q_i^L and q_i^U respectively.

The first objective function represents joint displacement and is proportional to the deviation from the *neutral position*. The neutral potion is selected as a relatively comfortable posture, typically a standing position with arms at one's sides. q_i^N is the neutral position of a joint, and $\mathbf{q}^N$ represents the overall posture. Because some joints articulate more readily than others, a weight γ_i is introduced to stress the relative stiffness of a joint. The final joint displacement is given as follows:

$$f_{Joint\,displacement}(\mathbf{q}) = \sum_{i=1}^{n} \gamma_i \left(q_i - q_i^N \right)^2 \quad (2)$$

As an alternative to setting weights, the mass of each body segment, inherently included in potential energy, can provide a natural weighting factor. In this vein, we represent the primary segments of the upper body with five lumped masses: three for the lower, middle, and upper torso, respectively; one for the upper arm; and one for the forearm. The datum (point of zero potential) for each body segment is defined by the neutral position. Ref. 6 discusses the details of consequent function for delta potential energy.

3. MULTI-OBJECTIVE OPTIMIZATION

Minimizing multiple performance measures simultaneously requires the use of special MOO algorithms. Therefore, in this section, we provide a brief overview of MOO theory, formulations for MOO methods, and a novel approach for normalizing the human performance measures.

Given a vector of objective functions $\mathbf{f}(\mathbf{q}) = [f_1(\mathbf{q}), f_2(\mathbf{q}), \cdots, f_k(\mathbf{q})]^T$, the *feasible design space* $\mathbf{\Pi}$ is defined as the set $\{\mathbf{q} | g_j(\mathbf{q}) \le 0,\ j = 1, 2, ..., m\}$, where $g_j(\mathbf{q}) \le 0$ is an inequality constraint. The *feasible criterion space* $\mathbf{Z}$ is defined as the set $\{\mathbf{f}(\mathbf{q}) | \mathbf{q} \in \mathbf{\Pi}\}$. The point in the criterion space where all of the objectives have a minimum value simultaneously is called the *utopia point*. Typically, this point is unobtainable. The most common solution concept for MOO problems is *Pareto optimality*. A solution point is Pareto optimal if it is not possible to move from that point and improve at least one objective function without detriment to any other objective function. Alternatively, a point is *weakly Pareto optimal* if it is not possible to move from that point and improve all objective functions simultaneously.

The weighted sum method for MOO entails minimizing the following objective:

$$F = w_1 f_{\text{Joint displacement}}(\mathbf{q}) + w_2 f_{\text{Delta potential energy}}(\mathbf{q}) \quad (3)$$

The weighted sum method provides a sufficient condition for Pareto optimality; it always yields a Pareto optimal point. However, it cannot yield points on non-convex portions of the Pareto optimal set.

The weighted min-max approach entails solving the following problem:

$$\begin{aligned} &\text{Find: } \lambda \text{ and } \mathbf{q} \in R^{DOF} && (4) \\ &\text{to minimize: } \lambda \\ &\text{subject to: } w_1 f_{\text{Joint discomfort}}(\mathbf{q}) - \lambda \le 0 \\ &\qquad\qquad w_2 f_{\text{Delta potential energy}}(\mathbf{q}) - \lambda \le 0 \end{aligned}$$

Using (4) provides a necessary condition for Pareto optimality. That is, it enables one to capture all of the Pareto optimal points, even if the Pareto optimal set is non-convex, but it may yield points that are only weakly Pareto optimal as well.

Often, weights are used to indicate the relative significance of the different objectives and thus provide a single solution that incorporates one's preferences. However, they may also be varied consistently as a mathematical parameter to yield a series of solution points that represent the Pareto optimal set. The latter approach is taken in this study. (3) and (4) are solved using SNOPT [17], which utilizes the sequential quadratic programming method.

As suggested in Ref. 18, normalizing objective functions is advantageous with MOO. Consequently, the two objective functions are normalized using the following approach:

$$f^{norm} = \frac{f(\mathbf{q}) - f^{\circ}}{f^{\max} - f^{\circ}} \quad (5)$$

where f° is a component of the utopia point (the minimum value for an independent objective function). $F_i^{\max} = \max_{1 \le j \le k} F_i(\mathbf{q}_j *)$, where $\mathbf{q}_j *$ is the point that minimizes the j^{th} objective function. (5) results in values for f^{norm} that are approximately between zero and one.

Using (5) requires accurate determination of global function minima (components of the utopia point). The most common methods for global optimization are genetic algorithms, which are described in detail in Ref. 19. However, despite their ability to provide the global optimum, genetic algorithms can be prohibitively slow. Thus, we have developed a more efficient hybrid method, in which the gradient-based features of sequential quadratic programming and a genetic algorithm are combined. A special genetic algorithm that has been adopted for small population sizes is used [20]. Then, the member of each population with the highest fitness is selected and used as a starting point in the fast gradient-based algorithm. This point is refined and then returned to the genetic algorithm.

4. RESULTS

In this section, the problem in (1) is solved. First, each objective function is used independently, and the relationships between the two performance measures are studied. Then, MOO is used to aggregate the measures, and the consequent Pareto optimal sets are analyzed. Four target points in Cartesian space are used to represent the workspace are illustrated in Figure 2.

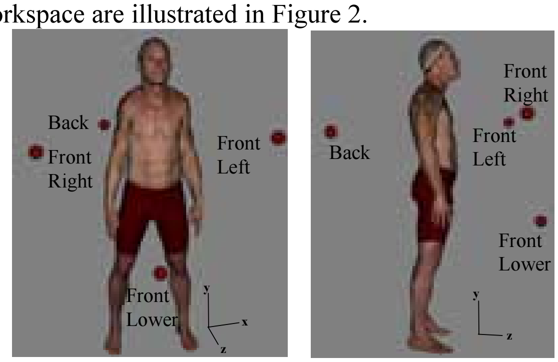

Figure 2: Target Points

The results when each objective function is minimized independently are studied using the front right target and the back target. The values of the objective functions are shown in Tables 1 and 2. Each row shows the values of the objective functions when one of the functions is minimized. Each column contains the values of a function at different postures. Clearly, these two objective functions oppose each other. In addition, the range of values for the two functions is significantly different, suggesting that the functions should be normalized if they are compared or combined.

The actual postures associated with the points in Tables 1 and 2, are shown in Figures 3 and 4. In evaluating the visual results, we are concerned primarily with gross movement; the nuances of skin deflection are not addressed. Generally, minimizing delta potential energy results in increased torso rotation about the vertical axis. Using delta potential energy also results in more bending of the elbow. Delta potential energy should not necessarily be used alone. This suggests that *human posture is not governed primarily by potential energy*, but as we show, potential energy does play a role. This finding is counterintuitive and consequently significant.

	Joint Disp.	Delta Pot. Energy
Min Joint Disp.	1.55835	26.95374
Min Delta Pot. Energy	176.13184	2.98259

Table 1: Objective Function Values, Front Right Target

	Joint Disp.	Delta Pot. Energy
Min Joint Disp.	2.15469	31.88572
Min Delta Pot. Energy	131.05643	1.68553

Table 2: Objective Function Values, Back Target

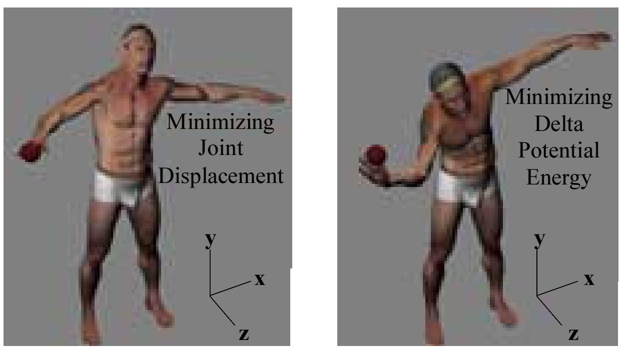

Figure 3: Postures with the Front Right Target

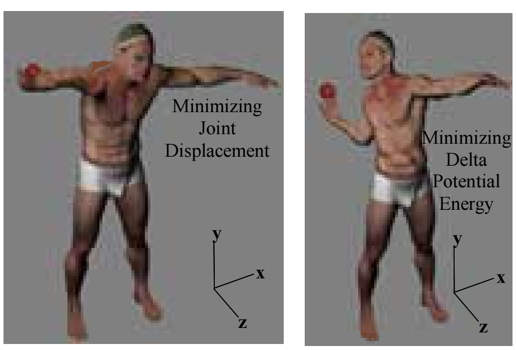

Figure 4: Postures with the Back Target

Testing reveals that delta potential energy does not always yield a unique solution point. There are many design points that result in the same function value, because there are many positions that all have the same potential energy value. This is especially true considering that the mass of the hand is not included in the potential energy formulation. Although the mass of the hand is relatively small, movement of the hand can result in slightly different postures that have the same value for potential energy. Practically, the potential for non-unique solutions reinforces the idea that delta potential energy should not be used alone. Thus, *in an effort to determine a unique solution, delta potential energy should always be coupled with another performance measure*.

We find that the appropriateness of delta potential energy depends on the location of the target, an idea that has significant repercussions in terms of task-based posture prediction. As shown in Figure 4, using delta potential energy can be advantageous when the target is behind the human model, because the delta potential energy allows for more twisting in the waist. Based on these results, the idea of task-based posture prediction can be refined. We have found that *performance measures should depend not just on the task being completed but where the task is completed, relative to the body*.

After evaluating the relative performance of the performance measures independently, they are considered in the context of a MOO problem. The performance measures are first normalized using (5). Values for f° and $f^{\max}$ are determined for each target point based on values such as those shown in Tables 1 and 2. A convex combination of functions is used such that $w_i \geq 0$ and $w_1 + w_2 = 1$. Two Pareto optimal sets are shown in Figures 5 and 6.

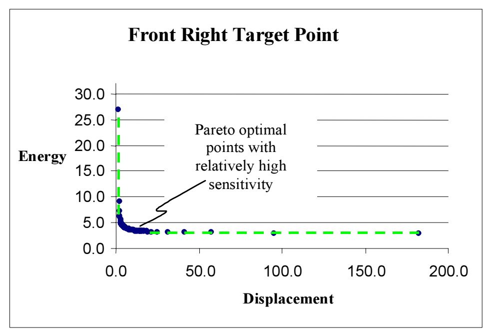

Figure 5: Pareto Optimal Set Using Weighted Sum with the Front Right Target

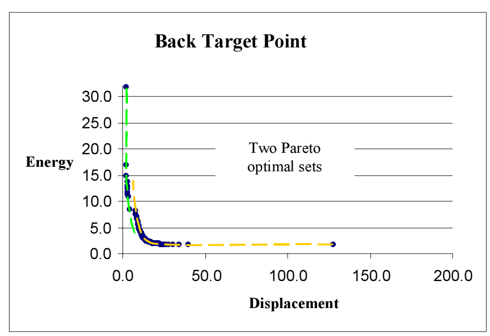

Figure 6: Pareto Optimal Sets Using Weighted Sum with the Back Target

Similar trends were seen with other target points. The gaps are simply a result of the number of points that are used. By studying the Pareto optimal set as a whole, we can gain insight into posture prediction and simplify the decision as to which Pareto optimal solution is most appropriate.

The Pareto optimal sets indicate function *trade-offs*. Assuming we view the set as a type of reduced feasible space, a trade-off indicates how much one function increases if we choose to reduce the other function by a certain amount. In other words, the Pareto optimal set indicates the sensitivity of one function to the other. In this context, this problem involves a special form of the Pareto optimal set. Note that for the dashed lines indicated in Figure 5, the value of one of the objective functions is approximately constant. That is, one function can be reduced with approximately no detriment to the other. These lines represent points that are approximately weakly Pareto optimal and thus irrelevant for all practical purposes. Such points are provided when one of the weights in the weighted sum is significantly higher than the other weight. Thus, w*eights with significantly different magnitudes should not be used when combining the normalized versions of joint displacement and delta potential energy*. This characteristic in the Pareto optimal set surfaces with all of the targets. Consequently, we show that *different targets do not have a significant effect on the general nature of the Pareto optimal set*, although the ranges for the function-values may change.

Notice that in Figure 6 there seem to be two separate Pareto optimal curves. This is a result of gradient-based optimization algorithms, which only yield local optima. Consequently, it is possible to find a solution point that is only locally Pareto optimal. Although the two sets of points do not represent significantly different objective-function values, this trend suggests that it may be beneficial to use a global optimization algorithm for determining the Pareto optimal set.

Figure 7 shows the results for the front right target when the weighted min-max method is used. When compared with Figure 5, it is clear that the two MOO methods provide similar Pareto optimal sets. This trend was evident with the other target points as well. Despite the fact that the weighted sum method provides a sufficient condition for Pareto optimality, while the weighted min-max method provides a necessary condition, *the weighted sum and weighted min-max methods illustrate the Pareto optimal sets for this problem with equivalent effectiveness*.

Some of the points in Figure 7 are used to compare different postures for a single target. Preferences, in terms of which function is more significant, are modeled by varying the weights, and the resulting postures are shown in Figure 8, with noted weights. Clearly, *different weights, which yield different Pareto optimal points, result in significantly different postures*. By comparing Figures 3 and 8, one can see the consequence of gradually increasing the degree to which delta potential energy is considered. As the significance of the delta potential energy is increased, there is an increase in bending of the torso and a subsequent reduction in the realism of the predicted posture. However, introducing delta potential energy to joint displacement as a minor component improves the result by reducing the height of the elbow slightly. Thus, *we show that the most realistic posture results from a minor consideration of potential energy*.

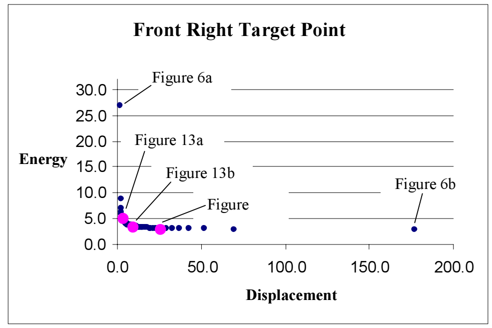

Figure 7: Pareto Optimal Set Using Weighted Min-max with the Front Right Target

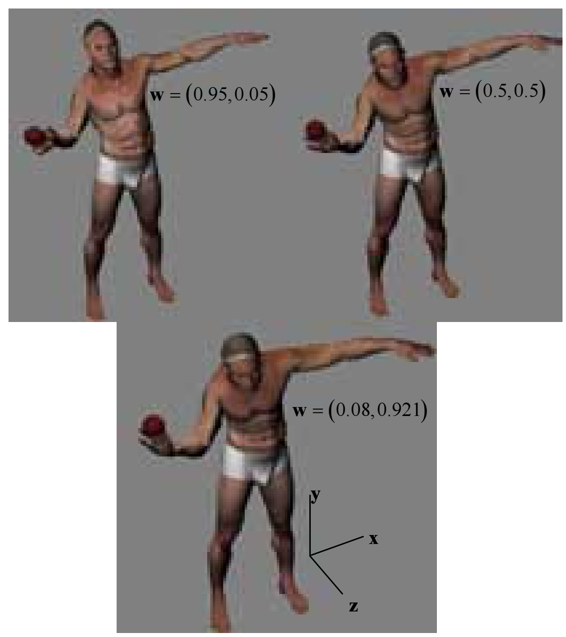

Figure 8: Postures Using the Weighted Min-max Method with the Front Right Target

5. DISCUSSION AND CONCLUSIONS

In this paper, we have used multi-objective optimization to study human posture and to advance posture prediction. Pareto optimal sets have been presented as a new analysis tool, indicating various features of the posture prediction problem. In this vein, we have identified and exploited a special form of the Pareto optimal set, and we have investigated the sensitivity of this form to changes in the target. By evaluating postures at various Pareto optimal points, we have studied the sensitivity of human posture to shifts along the Pareto optimal curve and to varying degrees of emphasis on the two performance measures.

The primary conclusions based on this study are: (1) Human posture does not depend heavily on potential energy. Nonetheless, the delta potential energy performance measure yields useful results as a component of a multi-objective performance measure, especially when used for targets behind the human. It should always be coupled with another objective, in order to reduce the likelihood of non-unique solutions. (2) The location of a task, in addition to the general nature of a task, should be factored into the process of task-based posture prediction. Different zones around the human require different performance measures. (3) The general form of the Pareto optimal set tends to be independent of the target location. (4) When weights are used, they should not have significantly different orders of magnitude. (5) The presence of local minima (rather than global minima) can play a significant role with some targets. (6) There is no significant difference between the Pareto sets provided by the weighted sum method and the weighted min-max method.

This study has flushed out potential areas for additional work. Genetic multi-objective algorithms need to be considered and their results compared to those of gradient-based algorithms. The actual postures for the two different Pareto optimal sets depicted in Figure 6 should be evaluated to study the differences between various local solutions. In addition, a similar study should be conducted with non-unique minima for the delta potential energy to determine how different the postures are for such minima. The mass of the hand should be considered in the delta potential energy, and the consequent effects on the existence of non-unique solutions should be evaluated. Finally, the postures resulting from various combinations of performance measures need to be validated.

REFERENCES:

[1] J. Zhao, & N.I. Badler, Inverse Kinematics Positioning Using Nonlinear Programming for Highly Articulated Figures, *ACM Transactions on Graphics, 13*(4), 1994, 313-336.

[2] V. Riffard, & P. Chedmail, Optimal Posture of a Human Operator and CAD in Robotics, *Proceedings of the IEEE International Conference on Robotics and Automation*, Minneapolis, MN, 1996, 1199-1204.

[3] Yu, W., *Optimal Placement of Serial Manipulators*, Ph.D. Dissertation, University of Iowa, Iowa City, IA, 2001.

[4] Z. Mi, J. Yang, K. Abdel-Malek, J.H. Mun, & K. Nebel, Real-Time Inverse Kinematics for Humans, *Proceedings of the ASME Design Engineering Technical Conferences and Computer and Information in Engineering Conference, 5A*, September, Montreal, Canada, 2002, 349-359.

[5] Z. Mi, *Task-Based Prediction of Upper Body Motion*, Ph.D. Dissertation, University of Iowa, Iowa City, IA, 2004.

[6] J. Yang, R. Marler, H. Kim, J. Arora, & K. Abdel-Malek, Multi-objective Optimization for Upper Body Posture Prediction, *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, August, Albany, NY, 2004.

[7] X. Zhang, & D.B. Chaffin, Task Effects on Three-Dimensional Dynamic Postures During Seated Reaching Movements: An Analysis Method and Illustration, *Proceedings of the 1996 40th Annual Meeting of the Human Factors and Ergonomics Society*, Philadelphia, PA, 1996, 594-598.

[8] B. Das, & D.N. Behara, Three-Dimensional Workspace for Industrial Workstations, *Human Factors, 40*(4), 1998, 633-646.

[9] J.J. Faraway, X.D. Zhang, & D.B. Chaffin, Rectifying Postures Reconstructed from Joint Angles to Meet Constraints, *Journal of Biomechanics, 32*, 1999, 733-736.

[10] D.B. Chaffin, On Simulating Human Reach Motions for Ergonomic Analysis, *Human Factors and Ergonomics in Manufacturing, 12*(3), 2002, 235-247.

[11] A. Liegeois, Automatic Supervisory Control of the Configuration and Behavior of Multibody Mechanism, *IEEE Transactions on Systems, Man and Cybernetics, SMC-17*(2), 1977, 868-871.

[12] C.A. Klein, & C.-H. Huang, Review of Pseudoinverse Control for Use with Kinematically Redundant Manipulators, *IEEE Transactions on Systems, Man, and Cybernetics, SMC-13*(3), 1983, 245-250.

[13] E.S. Jung, D. Kee, & M.K. Chung, Upper Body Reach Posture Prediction for Ergonomic Evaluation Models, *International Journal of Industrial Ergonomics, 16*, 1995, 95-107.

[14] X. Zhang, A.D. Kuo, & D.B. Chaffin, Optimization-Based Differential Kinematic Modeling Exhibits A Velocity-Control Strategy for Dynamic Posture Determination in Seated Reaching Movements, *Journal of Biomechanics, 31*, 1998, 1035-1042.

[15] M.P. Reed, M.A. Manary, C.A.C. Flannagan, & L.W. Schneider, Comparison of Methods for Predicting Automobile Driver Posture, *SAE 2000 Digital Human Modeling for Design and Engineering Conference and Exposition*, June, Detroit, MI, SAE paper 2000-01-2180, 2000.

[16] J. Denavit, & R.S. Hartenberg, A Kinematic Notation for Lower-Pair Mechanisms Based on Matrices, *Journal of Applied Mechanics, 22*, 1955, 215-221.

[17] P. Gill, W. Murray, & A. Saunders, SNOPT: An SQP Algorithm for Large-Scale Constrained Optimization, *SIAM Journal of Optimization, 12*(4), 2002, 979-1006.

[18] R.T. Marler, & J.S. Arora, Function-Transformation Methods for Multi-objective Optimization, *Engineering Optimization*, in press.

[19] R.T. Marler, & J.S. Arora, Survey of Multi-Objective Optimization Methods for Engineering, *Structural and Multidisciplinary Optimization, 26*(6), 2004, 369-395.

[20] D.L. Carrolll, web page, http://cuaerospace.com/carroll/ga.html.