New Capabilities for Vision-based Posture Prediction

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ABSTRACT

Although field of view (FOV) is a commonly used evaluation parameter with digital human models, minimal research has involved modeling how eye motion (relative to the head and body) affects the FOV and posture of a digital human striving to see a particular target. Few models incorporate independent eye movement and the effects of obstacles, with the ability to predict human posture realistically. This work presents two new and critical components for simulating how vision affects human posture: 1) inclusion of eye movement and 2) visual obstacle avoidance. This work is conducted using Santos™, a real-time predictive physics-based virtual human with a high number of degrees-of-freedom. With optimization-based posture prediction, joint angles serve as design variables used to minimize various human performance measures that provide objective functions, subject to constraints that represent biomechanical limitations and task characteristics. Vision-based objective functions and constraints are developed and easily implemented in order to accurately predict postures. First, two new degrees of freedom were added to the Santos™ model, representing vertical and horizontal movement of the eyes. Then, functions for eye movement relative to the head and body were developed based on experimental data. The new vision-based objective function expanded on the current vision model by incorporating these new functions. Additionally, a vision-based obstacle avoidance constraint was added in order to predict postures that incorporate the tendency to look around obstacles that may be in one's line of site. Although vision alone does not govern one's posture, when combined with other performance measures, more realistic predicted postures incorporating vision were obtained. Initial subjective validation suggests the predicted postures are accurate and realistic. The consequent capabilities have proven extremely useful for ergonomic studies and analyses of automotive cab scenarios.

Keywords: Optimization, Posture Prediction, Vision, Digital Human Modeling

INTRODUCTION

The field of digital human modeling is constantly striving to provide biomechanically accurate solutions for engineering design and analysis, especially for ergonomic studies. This becomes especially apparent during ergonomic studies of automotive cabs. In order to simulate human behavior realistically, an accurate vision model is essential. However, modeling human vision and the effects it has on performance can be complex. Consequently, this work concentrates on the motion of the body, neck, and eyes, in an effort to create a clear line of sight. Nonetheless, considering such factors requires an advanced human model that includes not just head and neck motion but eye motion as well, all coupled with the ability to predict human behavior.

This paper presents a new vision model, in the context of optimization-based posture prediction. This model combines real-time posture prediction, eye movement, and the ability to look around, or to the side of objects that may interfere with one's vision.

Although much work has been completed with studying vision, most current vision models are data based. There is little work that provides a mathematical model for predicting human posture, while considering the need to see a specified target. Many studies and experiments concentrate on the coordination between the eyes and head while gazing. These studies focus on incorporating the results into robot vision (Maini, 2006; Guitton and Volle, 1987). However, there is minimal research incorporating head-eye movement ratios in human vision models. Some authors, however, have investigated eye range-of-motion (ROM) (Guitton and Volle, 1987; Huaman and Sharpe, 1993). Guitton and Volle (1987) concluded that there are neural impulses during gaze shifts that prevent the eyes from reaching these limits at all times suggesting a coordination between the head and eye movements to obtain the visual sight of the target.

Kim (2007) provides one of the first works that includes vision in a predictive virtual human. He explores the modeling of head and eye coordination and finds that vertical and horizontal head-eye movement ratios are non-linear functions dependent on the location of the target. Non-linear equations are developed from existing data in order to predict the angle of three different head degrees of freedom: horizontal rotation, vertical flexion/extension, and cyclotorsion. The calculated head and neck joint angles were contrasted with the inverse kinematics algorithms built in Jack™ for similar target location, and more natural appearances were reported for head and neck angles.

Although much work has been completed regarding predictive capabilities for virtual humans, there are few, if any computational models that incorporate eye movement in posture prediction. Marler *et al* (2009) provides extensive reviews of posture prediction capabilities, and although there are a variety of performance measures incorporating joint angles, none actually include DOFs for eyes. Nonetheless, some authors do incorporate the tendency to try to see targets, by considering body and neck motion with the eyeballs essentially looking straight ahead. In this vein, Marler *et al* (2006) describe two vision performance measures (objective functions within the context of optimization-based posture prediction): visual displacement and visual acuity. These performance measures are based solely on head position and do not include eye movement. Smith *et al* (2008) analyze posture prediction using these head-based vision performance measures and joint displacement, and discover that vision alone does not govern posture prediction. Consequently, the authors study the use of vision-based performance measures combined with other objective functions such as joint displacement, and implemented as constraints.

Most current digital human models do not include eye movement and depend primarily on head orientation to predict postures that incorporate vision. Some models include vision cones stemming from the head showing primary and periphery vision zones (Hanson, 1999).

MODEL DEVELOPMENT

The work presented in this paper uses the Santos™ human model as a platform for further development (Abdel-Malek *et al* 2006; Marler *et al*, 2008). The underlying skeletal structure for Santos™ is modeled as a series of links with each pair of links connected by one or more revolute joints. There is one joint angle for each DOF. The relationship between the joint angles and the position of points on the series of links (or on the actual avatar) is defined using the Denavit-Hartenberg (DH)-method (Denavit and Hartenberg, 1955).

Postures are predicted using an optimization-based approach detailed by Farrell et al (2005). Joint angles are the design variables, which are incorporated in various objective functions and constraints, formulated as follows:

$$\begin{aligned}
&\text{Find: } \mathbf{q} \in R^{DOF} \\
&\text{To minimize: } f(\mathbf{q}) \\
&\text{Subject to: Distance} = \left\| \mathbf{x}(\mathbf{q})^{\text{end-effector}} - \mathbf{x}^{\text{target point}} \right\| \le \varepsilon \\
&q_i^L \le q_i \le q_i^U;\ i = 1, 2, \ldots, DOF
\end{aligned} \tag{1}$$

Where q is a vector of joint angles, x is the position of an end-effector or point on the avatar, and ε is a small positive number that approximates zero and DOF is the total number of degrees of freedom. $f(q)$ can be one of many performance measures. The primary constraint, called the *distance* constraint, requires the end-effector to contact a specified target point. q_i^U represents the upper limit, and q_i^L represents the lower limit. These limits are derived from anthropometric data.

The new eye displacement performance measure expands on the visual displacement performance measure described by Marler et al (2006), and is developed in the context of the basic optimization-based posture prediction problem formulated in (1). Visual displacement ensures that an eye vector, which emanates from the eye perpendicular to the face of Santos™ successfully, intersects the target. It essentially minimizes the absolute value of γ_{Eye_Tar} which is defined as the angle between the eye vector and the target vector (See FIGURE 2). Details of this objective function are provided by Marler et al (2006).

The new eye displacement performance measure uses visual displacement as a foundation and incorporates two new functions representing the vertical and horizontal eye displacement. In general, this performance measure ensures that literature based head-eye movement ratios are satisfied while still utilizing the old vision model to ensure that the eye vector intersects the target.

The performance measure required two new degrees of freedom to be added to Santos's™ skeleton. New axes of rotation representing vertical and horizontal DOFs for the eyes were implemented, and literature-based (Guitton and M.Volle 1987) (Huaman and Sharpe 1993) joint limits were added. The new eye displacement performance measure calculates γ_{Eye_Tar} using the new eye vector (FIGURE 1) that has a base between Santos's™ eyes and depends on the orientation of the eyes instead of solely the head orientation as with the previous eye vector.

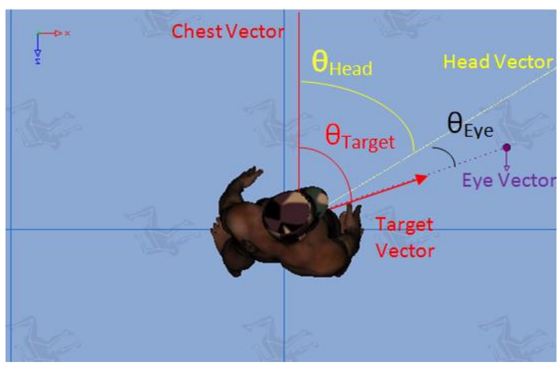

FIGURE 1 Angle and vector definitions.

All angles in FIGURE 1 are dependent on the current posture of Santos™ and thus are functions of *q*. The chest vector is defined as the orientation of Santos's™ upper-most spine joint and is used to represent the midsagittal plane. The head and eye vectors are defined by the orientations of the head and eyes respectively. The target vector represents the position of the target. θ_{Head} is the horizontal angle between the chest and head vectors, and θ_{Eye} is the horizontal angle between the head and eye vectors. θ_{Target} is the total horizontal target displacement from the midsagittal plane chest vector to the target vector. Using these angles and interpreting the head contribution ratio data (Kim, 2007), which depends on the θ_{Target}, eye contribution ratios were calculated and are shown in **Table 1**. θ is the horizontal component of the angles and ϕ is the vertical component of the angles. ϕ_{Target} is calculated from the horizontal plane at Santos's™ eye level (eye plane) to the target and represents vertical target displacement.

Table 1 Percentage of Eye Contribution Depending on Target Displacement

Horizontal	θ_{Eye} %	Vertical	ϕ_{Eye} %
$0° \le \theta_{Target} \le 10°$	100	$0° \le \phi_{Target} \le 19°$	84
$\theta_{Target} \ge 10°$	32	$\phi_{Target} \ge 19°$	29

From these head-eye ratios, distinct non-linear horizontal and vertical functions were developed. The literature values for θ_{Head} and ϕ_{Head} depending on θ_{Target} and ϕ_{Target} are represented by the red lines in FIGURE 2 (Kim, 2007). The y-axis represents the head angle (radians), and the x-axis represents the total target displacement (radians).

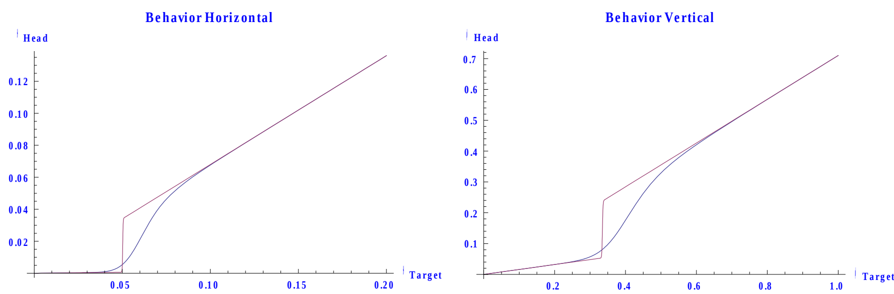

FIGURE 2 Continuous functions developed (blue line) to represent the literature model of the head angles (red line).

The literature based functions are discontinuous; therefore, two new continuous function approximations were developed, represented by the smooth blue lines in FIGURE 2. Both of these smooth functions can be represented as follows with different coefficients α, μ, β, ω, and η:

$$\theta_{Head-Desired} = f(\theta_{Target}(q)) = \alpha \frac{\theta_{Target}(q)}{(\mu + \theta_{Target}(q))^{\beta} + \eta} + \omega \theta_{Target}(q) \qquad (2)$$

$\theta_{Head\text{-}Desired}$ is calculated using (2) with α= -4, μ=20, β=10, ω= 0.68, and η=6. $\phi_{Head\text{-}Desired}$ is also calculated using (2) but with ϕ_{Target} substituted for θ_{Target} and with α= -3.3, μ= 3, β= 10, ω= 0.71, and η= 6. $\theta_{Head\text{-}Desired}$ and $\phi_{Head\text{-}Desired}$ are the desired head angles and are used to find the $\theta_{Eye\text{-}Desired}$ and $\phi_{Eye\text{-}Desired}$ by subtracting $\theta_{Head\text{-}Desired}$ and $\phi_{Head\text{-}Desired}$ from θ_{Target} and ϕ_{Target} respectively. Therefore, the two new components of the vision model minimize the difference between the $\theta_{Eye\text{-}Desired}$ and $\phi_{Eye\text{-}Desired}$ and the measured values of $\theta_{Eye}(q)$ and $\phi_{Eye}(q)$. The complete objective function that represents the relationship between the vertical and horizontal eye movement as well as the tendency for the eye vector to coincide with the target is given as follows:

$$f_{EyeDisp}(q) = \left[\theta_{Eye}(q) - (\theta_{Target}(q) - \theta_{Head-Desired})\right]^2 + \left[\phi_{Eye}(q) - (\phi_{Target}(q) - \phi_{Head-Desired})\right]^2 + \gamma_{Eye\_Tar}(q)^2 \quad (3)$$

The first term of (3) ensures that the horizontal eye angle equates to the literature-based horizontal eye angle; the second term ensures that the vertical eye angle equates to the literature-based vertical eye angle; and γ_{Eye_Tar} utilizes the previous vision displacement objective function to ensure that the eye vector intersects the target.

The vision objective function in (3) is used as the objective function in (1) and generates posture solutions that enable the avatar to look at the target while predicting postures. However, the avatar must also able to detect obstacles obstructing the eye vector. Towards this goal, an additional vision obstacle avoidance constraint has been developed and incorporated in the predictive vision model. This constraint leverages the work of Johnson et al (2009) and ensures that the eye vector does not pass through any object in the scene.

As part of the posture prediction process, all geometry in the virtual environment is represented with sphere-based surrogate geometry (Johnson, et al. 2009). The constraint ensures that the distance between the eye vector and the eye-to-sphere vector is greater than the radius of the obstacle sphere using:

$$\left|x - p(q)\right|^2 \sin^2\theta - r^2 > 0 \quad (4)$$

where, x is a specific obstacle sphere with radius r, $p(q)$ is the position of the eyes, and θ is the angle between the eye vector and the eye-to-sphere vector. This constraint ensures that the distance between the eye vector and the eye-to-sphere vector (defined by term 1 in (4)) minus the radius is greater than zero.

The final formulation for the new vision model includes one obstacle avoidance constraint for each sphere representing surrogate geometry, and includes (3) as the objective function.

RESULTS

In this section, we demonstrate the advantages of the new vision model, with respect both to incorporation of eyes and to consideration of obstacle avoidance. Two sets of basic tests were run, followed by a test in a practical setting. First, we verified that the data used in FIGURE 2 is represented in the final predicted postures. Secondly, we compare results using the previous vision model with results using the new model that now incorporates eyes. Finally, we subjectively verify the accuracy of the predicted postures in a practical cab setting. Note that with these tests, a weighted sum of the eye displacement and joint displacement (Marler, 2009) was used as the objective functions, with weights of 0.99 and 0.01 respectively. Thus, the vision performance measure was isolated, but the use of joint displacement resulted in more realistic results for limbs.

FIGURE 3 Isolating the horizontal eye movement with a target displaced 80° (a. and b. Target located at (-714, 765, -96) in mm) and 12° (c. and d. Target located at (-37, 765, -355) in mm) from the midsagittal plane. a. and c. use the old vision model and b. and d. use the new vision model.

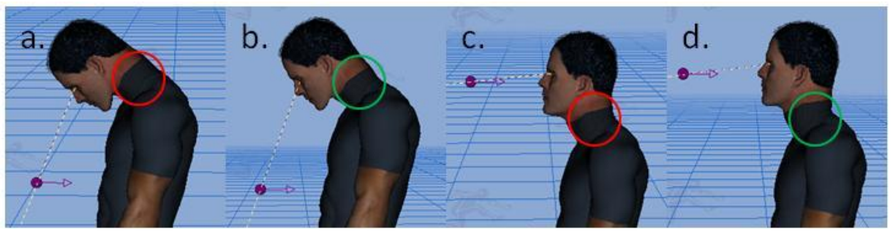

FIGURE 4 Isolating the vertical eye movement with a target displaced 71° (a., b. Target (0, 279, -317) mm) and 14° (c., d. Target (0, 715, -383) mm) from the horizontal eye plane. a., c. use the old vision model and b., d. use the new model.

Table 2 Literature Value Vadidation (*Represents Literature Values)

Figure	γ_{Target} (°)	γ_{Eye}%	γ_{Eye}%*
3b	80	32	32
3d	12	91	100
4b	71	29	29
4d	14	84	84

As Table 2 demonstrates, the predicted percentage of eye angle contribution represents closely the underlying data. One exception is shown in FIGURE 3d, where for horizontal eye displacement values from 0° to 10°, the percentage of eye movement should be 100%. This discrepancy is explained by the inherent approximation made to the original curve to remove discontinuities, as shown in FIGURE 2. However, the discrepancy translates to a difference of only one degree.

When comparing the previous vision model to the new model, FIGURES 3a and 3b provide an example of the added functionality that the new model provides. With the spine frozen and using the old vision displacement model, there is no feasible solution, and this is unrealistic. With the new eye displacement objective function (FIGURE 3b), Santos™ can easily see the target by moving his eyes.

Using only a small horizontal target displacement with the new objective function (FIGURE 3d) results in postures that are not as realistic as the previous visual displacement model (FIGURE 3c). Santos™ moves his head farther to the right and uses his eyes to look back to the left to see the target. This results from the formulation only ensuring that $\theta_{Eye\text{-}Desired}$ is equated to $\theta_{Eye}(q)$, but not ensuring that the $\theta_{Head\text{-}Desired}$ is equated to $\theta_{Head}(q)$. In most cases $\theta_{Eye\text{-}Desired}$ being equal to $\theta_{Eye}(q)$ produces solutions with $\theta_{Head}(q)$ being approximately equal to $\theta_{Head\text{-}Desired}$ as well. However, in cases with small target displacements and small $\theta_{Head\text{-}Desired}$, excess head movement where $\theta_{Head}(q)$ is greater than $\theta_{Head\text{-}Desired}$ can also result in postures with $\theta_{Eye\text{-}Desired}$ equal to $\theta_{Eye}(q)$. Since vision alone does not typically govern human posture, adding a greater weight to the joint displacement objective function may solve this problem by minimizing excess head movement.

In FIGURE 4b isolating a large vertical target displacement, using the new eye displacement objective function results in a more realistic posture that causes less movement and strain on the head and neck of Santos™. In FIGURE 4d, the resulting solutions demonstrate that with small vertical displacements, there are minimal differences between postures generated by the visual displacement or eye displacement models.

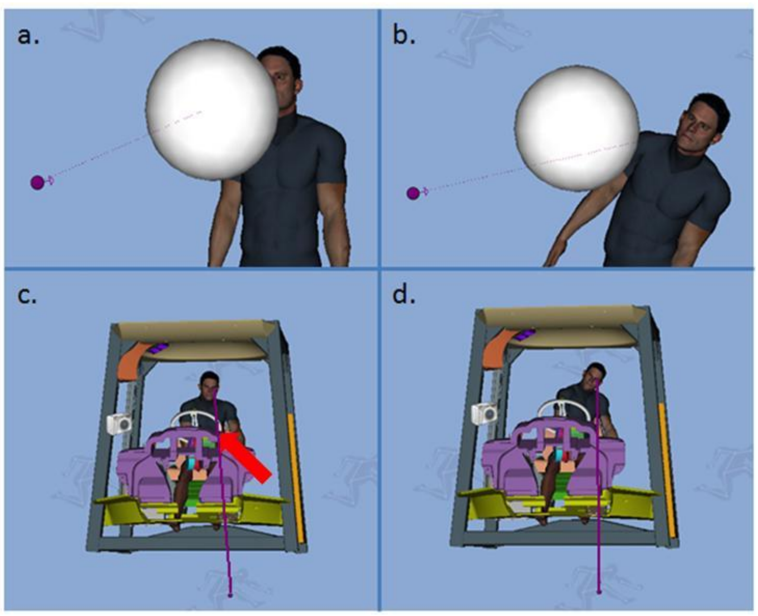

FIGURE 5 Implementation of the obstacle collision avoidance constraint with real world applications. a., c (collision shown by red arrow) use the old vision model and b., d. use the new model.

Following the above-mentioned basic tests, the new model was evaluated in the context of a cab setting. Clearly, as shown in FIGURE 6, incorporating eye movement results in more realistic postures. FIGURE 5 shows the difference in postures when using the vision obstacle avoidance constraints. Santos™ looks around obstacles that are obstructing his line of sight.

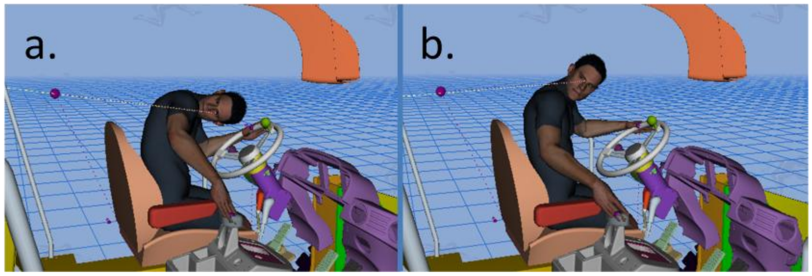

FIGURE 6 Real world application using a. the old vision model b. the new vision model

CONCLUSION

This paper demonstrates a new predictive vision model that includes eye movement and the ability to look around objects that obstruct one's view. Incorporating eye movement involved the deceptively complex task of modeling how one naturally distributes motion between the body, the neck, and the eyes. The results were tested and validated subjectively. Although we find that the proposed model is a substantial improvement over previous results, this improvement is less distinct for targets requiring minimal overall angular displacement. In a few rare cases, the results with the new model are not as realistic as those with the previous model. This detriment is attributed in part to the necessity for combing any vision objective-function with another function that represents overall body posture, using multi-objective optimization (Marler et al, 2009). That is, vision alone cannot be used as a complete posture-prediction model. It is, however, a critical component.

Although the overall approach to simulating human posture is predictive, independent of predetermined data, the model for incorporating eyes is in fact data based. Despite the initial success of the proposed model, future work will entail further investigation of mathematical models complementing the data-based aspect. To this end, the fundamental formulation for posture prediction, on which this work is based, allows us to study what governs posture (and vision) by experimenting with various performance measures and constraints. It allows us to model and test various hypotheses. In addition, various means of controlling eye and head orientation will be investigated. Initial studies suggest that combing vision with a performance measure like joint displacement have been successful in this regard. Focal views or vision cones of different types of vision tasks such as gazing, reading, or peripheral sight could be incorporated into the model. Such work would also include adding the third degree of freedom of the eyes: rotational torsion. Finally, although subjective tests and mathematical comparisons to literature values have validated initial results, a more thorough validation study including motion capture and an eye-tracking device will be conducted.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge project funding from Caterpillar Inc.

REFERENCES

Abdel-Malek, K., Yang, J., Marler, T., Beck, S., Mathai, A., Zhou, X., Patrick, A., and Arora, J. (2006), "Towards a New Generation of Virtual Humans," *International Journal of Human Factors Modelling and Simulation*, 1 (1), 2-39.

Denavit, J., and R. S. Hartenberg. "A Kinematic Notation for Lower-pair Mechanisms Based on Matrices." *Journal of Applied Mechanics,* 77 (1955): 215-221.

Farrell, K., Marler, R. T., and Abdel-Malek, K. (2005), "Modeling Dual-Arm Coordination for Posture: An Optimization-Based Approach," *SAE 2005 Transactions Journal of Passenger Cars - Mechanical Systems*, 114-6, 2891, SAE paper number 2005-01-2686.

Guitton, D. and Volle, M. (1987). "Gaze Control in Humans: Eye-Head Coordination During Orienting Movements to Targets Within and Beyond the Oculomotor Range." *Journal of Neurophysiology*. 58, 427-459.

Hanson, Lars, and Akselsson, Roland. (1999). "ANNIE, a Tool for Integrating Ergonomics in the Design of Car Interiors." *SAE Souther Automotive Manufacturing Conference*, September, Birmingham, Alabama.

Huaman, Ana and Sharpe, James. (1993), "Vertical Saccades in Senescence." *Investigative Ophthalmology & Visual Science*, 34, 2588 – 2595.

Johnson, R., B. L. Smith, R. Penmatsa, T. Marler, and K. Abdel-Malek. (2009) "Real-Time Obstacle Avoidance for Posture Prediction." *3rd International Conference on Applied Human Factors and Ergonomics.* Miami: AHFE International.

Kim, Kyung Han, R. Brent Gillespie, Bernard J. Martin. (2007). "Head Movement Control in Visually Guided Tasks: Postural Goal and Optimality" *Computers in Biology and Medicine*. 37, 1009-1019.

Maini, Eliseo Stefano, Giancarlo Teti, Michele Rubino, Cecilia Laschi, Paolo. (2006) "Bio-inspired control of eye-head coordination in a roboitc anthropomorphic head." *International Conference on Biomedical Robotics and Biomechanics*. 549.

Marler, R. T., Arora, J. S., Yang, J., Kim, H. –J., and Abdel-Malek, K. (2009), "Use of Multi-objective Optimization for Digital Human Posture Prediction," *Engineering Optimization*, 41(10), 295-943.

Marler, T., Arora, J., Beck, S., Lu, J., Mathai, A., Patrick, A., Swan, C. (2008), "Computational Approaches in DHM," in *Handbook of Digital Human Modeling for Human Factors and Ergonomics*, Vincent G. Duffy, Ed., Taylor and Francis Press, London, England.

Marler, R. T., Farrell, K., Kim, J., Rahmatalla, S., Abdel-Malek, K. (2006). "Vision Performance Measures for Optimization-Based Posture Prediction." *SAE Digital Human Modeling for Design and Engineering Conference,* July, Lyon, France, Society of Automotive Engineers, Warrendale, Pennsylvania.

Smith, Brian Lewis, Marler, R. T., Abdel-Malek K. (2008). "Studying Visibility as a Constraint and as an Objective for Posture Prediction." *Digital Human Modeling for Design and Engineering Symposium,* June Pittsburgh, Pennsylvania.