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Studying Visibility as a Constraint and as an Objective for Posture Prediction

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ABSTRACT

Using optimization to predict human posture provides a unique means of studying how and why people move. In a formulation where joint angles are determined in order to minimize a human performance measure subject to various constraints, the general question of when to model components as objective functions and when to model them as constraints has not been addressed thoroughly. We suggest that human performance measures, which act as objective functions, model what drives human posture, whereas constraints provide boundary conditions that restrict the scope of the model. This applied research study tests this hypothesis and concurrently evaluates how vision affects the prediction and assessment of upper-body posture. Single-objective and multi-objective optimization formulations for posture prediction are used with a 35 degree-of-freedom upper-body model of a virtual human called Santos™. Vision is modeled as an objective function or as a constraint, and these two cases are tested in the context of standing reaching-tasks as well as reaching-tasks within a cab environment. Results are evaluated qualitatively in terms of predicted postures, and quantitatively in terms of values for various performance measures. We find that the proposed hypothesis is accurate. We also find that vision alone does not govern human posture and that the selection of specific performance measures and constraints is task based. Some scenarios require one to see a target, while others necessitate only trying to see a target. The function of restricting the scope of the model is only relevant with difficult tasks, where constraints are likely to be active. Consequently, performance when using vision as a constraint and as an objective is similar for targets that are relatively easy to see. The proposed vision constraint provides the capability to model tasks that require vision. It also allows one to conduct what-if studies and evaluate the human-performance consequences of forcing a subject to see a target.

INTRODUCTION

The objective of this paper is to compare different ways of modeling vision of a virtual human and how it affects upper-body posture. Vision is an important aspect of posture prediction, because humans typically strive to visualize what they are touching. Currently, there are two performance measures for modeling vision with the Santos™ virtual human: visual acuity and visual displacement. Santos™ is a comprehensive, highly realistic, biomechanically accurate predictive virtual human with variable anthropometry. A thorough explanation of the vision performance measures is provided by Marler *et al* (2006). In general, although visual acuity depends on a variety of elements, most relevant to posture is its inverse dependence on the angular distance of a target from the eye fovea, with a value of zero when outside one's peripheral vision. The visual acuity performance measure models this element. Alternatively, visual displacement is essentially the absolute value of the angular distance from fovea regardless of target location. The development of these performance measures includes basic experimental validation. The authors find that visual acuity has little effect on posture when the target point is outside the initial field of view. Thus, in this study, visual displacement is used to predict postures, although the values for both performance measures are recorded and discussed.

A vision constraint has been developed that allows the user to study cases where the avatar must look at the target regardless of how uncomfortable it may be or how extensive joint activity is. The methods analyzed here involve an optimization based approach to predicting human posture. Two test cases are applied to a number of different target points. For both test cases, the optimization problem is constrained by joint limits and distance between the end-effector and the target point. The visual displacement performance measure is used as either an objective function or a constraint. Target points are be analyzed, and final conclusions and recommendations are made.

The primary intent of this work is to compare results obtained with various pre-defined validated models. We are evaluating the performance of the vision-displacement model when used as an objective function and when used as a constraint. This evaluation is based on subjective visual inspection of predicted postures and on quantitative analysis of performance-measure values. Conducting experimental validation of the two uses is beyond the scope of this work.

LITERATURE REVIEW

Although many researchers have studied the cervical spine (the neck), the details of vision, the nature of eye movement, and even various characteristics of eye-hand coordination, little work has been completed that incorporates the tendency to look at what one is working with, in posture-prediction models. Mi (2004) and Marler *et al* (2005a) provide extensive reviews of posture-prediction capabilities. Here, we focus on upper-body optimization-based posture prediction and present work with modeling the neck through vision performance measures and a vision constraint. The vision performance measures are reviewed extensively by Marler *et al* (2006).

Although many studies concerning the neck and vision are experimental, some work has been completed with modeling. This kind of work originated with vision-based control of robots, a survey of which is provided by Hashimoto (2003). Ouefelli *et al* (1999) solve a system identification problem to determine the kinematic characteristics of the neck model that most accurately approximates given data. However, the model has only three DOFs, which the authors determine is too few. With the intent of studying the neural control of the neck, Mitelman and Enderle (2001) develop a model based on the neck muscular system and its relationship with the central nervous system. Zanasi *et al* (2002) provide a basic 3-DOF planar dynamic model of the neck for studying passenger head movements in an automobile. Kim *et al* (2004b) model the neck and vision in the context of a method for coordinating multiple subsystems, such as visual gaze and manual reach. Essentially, and inverse-kinematics approach to seated motion prediction is extended to solve the subsystem of each limb separately. The subsystems consist of a 9-DOF manual subsystem, which includes the torso and right arm, and an 8-DOF visual subsystem, which includes the torso and neck. The neck itself is composed of five DOFs. With respect to modeling vision, conceptually, the line of site is simply constrained to intersect the point of interest. A weighted pseudo-inverse of the Jacobian is used, and the weights are set such that the predicted motion approximates prerecorded motion. Given an inverse kinematics solution for each subsystem, a secondary objective is applied to reconfigure the shared joint angles, which occur in the torso.

Many authors have studied movement of the actual eye. Yamada (1991) studies eye-head coordination and finds that it is almost impossible to rotate or translate the head without tilting one's neck. In addition, when visual targets move more than thirty degrees away from the line of site, one tends to move one's eyes more than the head. Crowley *et al* (1995) develop models for simulating how the eyes fixate on a point. Drawing on observations from psychology, human factors, and computer vision, Chopra-Khullar and Badler (1999), and Gillies and Dodgson (2002) provide computational frameworks for modeling how an avatar reacts, in terms of eye movement, to the viewed or peripheral environment.

METHODS

This section provides an overview of the two test cases which were used to conduct this study. Test Case #1 was developed in order to isolate the visual displacement performance measure, whereas Test Case #2 used additional performance measures in an attempt to create more realistic postures.

TEST CASE #1

Test Case #1 uses three different optimization formulations to create postures and record performance-measure values. The purpose of Test Case #1 is to create postures using different optimization formulations, and to record performance measure values associated with the predicted postures. The optimization problems are kept simple with a small number objective functions in order to isolate the visual displacement performance measure. The testing method for Test Case #1 is as follows and is applied to all target points:

1. A single objective optimization (SOO) problem is formulated to minimize visual displacement. This SOO problem determines if vision alone governs human posture.
2. The right hand end-effector is set to a target point.
3. The predicted posture analyzed subjectively, and performance measures are recorded for quantitative comparison.
4. A multiple objective optimization (MOO) problem is formulated with visual displacement and joint displacement as the objective functions. Step 3 is repeated in order to compare the posture results of using vision as a performance measure and vision as a constraint. The MOO method used to combine the various objective functions is based on the work of Marler (2005).
5. Another SOO problem is formulated with joint displacement as the objective function and visual displacement as a constraint. Step 3 is repeated.

TEST CASE #2

For the second test case, a cab is loaded into Santos' environment. The presence of the cab allows target points to be specified as actual objects and not simply points in space. The optimization problem involves additional objective functions, all weighted equally. While Test Case #1 is useful to study vision, the ultimate goal in posture prediction is to develop the most realistic, human-like postures. Test case #2 uses more performance measures in the optimization formulation to create these more realistic postures. The testing method for Test Case #2 is given below and is applied to all target points. This method has been developed under the assumption that while inside the cab, typically one hand will be used to steer the vehicle and the other hand used to reach controls.

1. A MOO problem is formulated with visual displacement, joint displacement, potential energy, discomfort, and effort as the objective functions. This combination of objective functions was chosen because it created the most realistic postures. These performance measures are explained in detail by Yang *et al* (2004).
2. Both hands are placed on the steering wheel (this is the initial posture).
3. The right hand end-effector is placed on a point inside of the cab while the left hand remains placed on the steering wheel.
4. The target point for vision is set to the same point as the right hand in step 3.
5. Predicted posture is visualized and performance measures are recorded.

A MOO problem is created with joint displacement, potential energy, discomfort and effort as the objective functions. Visual displacement is added as a constraint. Steps 2 through 5 are repeated.

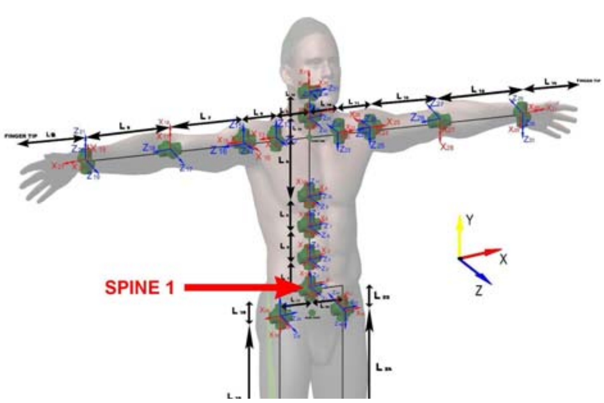

Figure 1: Location of Spine 1 joint (origin of all target points specified)

The next section shows the results gathered from Test Case #1 and Test Case #2. Images of actual postures as well as all performance measure data from the predicted posture are given.

RESULTS

TEST CASE #1

This section offers a set of figures corresponding to the predicted postures from the methods described for Test Case #1. Each figure has an associated table containing performance measure data, which provides a means for quantitative analysis. For each figure, the leftmost posture (i) corresponds to the SOO problem of visual displacement, the middle posture (ii) corresponds to the MOO problem of visual displacement and joint displacement, and the rightmost posture (iii) corresponds to the SOO problem of joint displacement with visual displacement added as a constraint. The coordinates of each target point are given in cm with respect to the SPINE 1 joint shown in Figure 1.

Figure 2: Postures (i), (ii) and (iii) for Target 1 (-50, 31, 47).

Before comparing performance measure values, we can determine a few things just by observing the postures in Figure 2. One interesting observation is the similarity between Figure 2(ii) and Figure 2(iii), both of which are more realistic than Figure 2(i). Because these postures are similar, there appears to be no difference between using visual displacement as an objective function and using visual displacement as a constraint.

TABLE 1: Performance measure values for Target 1

	Discomfort	Joint Disp.	Pot. Energy	Visual Acuity	Visual Disp.
(i)	114.73	44.0642	42.8298	1	0
(ii)	29.4848	2.0065	18.7057	0.9999	0
(iii)	29.3722	3.27	18.7082	0.9996	0.0001

Analysis of Table 1 verifies the notion that for this target point, it makes no difference whether visual displacement is used as an objective function or as a constraint. In all three cases, the vision performance measures, visual acuity and visual displacement, are never compromised. The posture in Figure 2(i) has the elbow and shoulder placement too high, while the postures in Figure 2(ii) and Figure 2(iii) are more realistic. The recorded values for effort, discomfort, joint displacement, and potential energy (non-vision-based performance measures) are all much higher for (i) than (ii) or (iii). It is evident that using visual displacement for SOO is not advisable. This is in agreement with the results of Marler *et al* (2006) and suggests that vision alone does not govern human posture.

The next section shows postures and performance measure values for the second target point which is placed behind and to the right of Santos™. Coordinates from Spine 1 are given below.

Figure 3: Postures (i), (ii) and (iii) for Target 2 (-35, 42, -30).

TABLE 2: Performance measure values for Target 2

	Discomfort	Joint Disp.	Pot. Energy	Visual Acuity	Visual Disp.
(i)	417.2913	115.3472	69.5392	1	0
(ii)	239.9239	12.2425	38.5606	0.9402	0.017
(iii)	253.3507	13.617	40.7519	0.9996	0.0001

The location of Target 2 is harder to see. Consequently, it results in more uncomfortable postures. Vision performance measures are fully optimized for Figure 3(i) but the remainder of the performance measures represents an uncomfortable posture. Figure 3(ii) is a greater improvement in posture, but there is a gap between the vision vector and the end-effector (tip of the index finger). Figure 3(iii) intersects the vision vector with the target point and is the most realistic posture for this target point. It is evident from Table 2(ii) that while using visual displacement as an objective function results in realistic postures, the vision performance measures are not optimal. In other words, Santos™ is in a relatively comfortable position, but he may not be able to see the target point clearly. For this target point, constraining visual displacement yields optimal vision performance measures without greatly increasing non-vision performance measures.

The next section shows postures and performance measure values for Target 4, which is placed to the lower right side of Santos™. Coordinates from Spine 1 are given below.

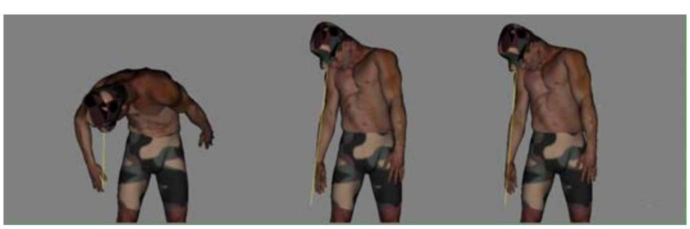

Figure 4: Postures (i), (ii) and (iii) for Target 4 (-26, -31, -8).

TABLE 4: Performance measure values for Target 4

	Discomfort	Joint Disp.	Pot. Energy	Visual Acuity	Visual Disp.
(i)	327.8544	72.2613	45.8048	1	0
(ii)	192.8271	3.1904	0.4406	0.9787	0.006
(iii)	195.4342	3.6998	0.4841	0.9996	0.0001

Again, for Target 4, (ii) and (iii) are similar except for the visual performance measures recorded in Table 4. Visual acuity and visual displacement are not fully optimized in (ii). Table 4(iii) optimizes these performance measures while keeping non-vision performance measures low.

Shown below are the postures and performance measure values for the final target of Test Case #1. The target is placed behind Santos™ and to the right.

Figure 5: Postures (i), (ii) and (iii) for Target 5 (-10, 10, -50).

TABLE 5: Performance measure values for Target 5

	Discomfort	Joint Disp.	Pot. Energy	Visual Acuity	Visual Disp.
(i)	509.8333	84.0687	43.7335	1	0
(ii)	289.0023	23.6198	34.2463	0.2236	0.4168
(iii)	437.9662	64.2671	34.7076	0.9996	0.0001

The last target for Test Case #1 is used to justify the conclusion that when targets are in places behind the avatar, the differences between modeling vision as an objective function and as a constraint become much more noticeable. In Figure 5(ii), the red vision vector is nowhere near the target. With such a low value for visual acuity and such a high value for visual displacement, Santos™ cannot see what he is touching. The addition of eyeball movement could improve this. In this case, there exists a noticeable change from (ii) to (iii), whereas when targets are placed in front of Santos, there is almost no change.

A summary of findings from the results of Test Case #1 is given next.

- Vision alone does not govern human posture.
- When target points are placed inside the initial field of view or in front of the avatar, there is little difference in using vision as an objective function or as a constraint.
- Placing target points to the sides of Santos™ also show little difference in using

vision as an objective function or as a constraint.

- If the task requires visualization, then vision should be used as a constraint. However, if the task does not require Santos™ to look at the target, then vision may be used as an objective function which results in more comfortable postures.
- Based on Test Case #1 we find that the decision to use vision as an objective function or as a constraint depends upon the task. We recommend that for tasks that require the avatar to look at the target, vision should be used as a constraint.
- For tasks that do not require the avatar to look at the target, vision may be used as an objective function. This method of using vision as an objective function results in more comfortable postures but vision is compromised.

TEST CASE #2

The remaining data was collected as part of the second test case using additional performance measures with multi-objective optimization. In contrast, Test Case #1 was designed to focus on visual displacement. For each of the figures below, the posture on the left (i) is obtained from a MOO problem involving visual displacement, joint displacement, potential energy, discomfort. The posture on the right (ii) is obtained from the MOO problem. For (ii), visual displacement is added as a constraint. All coordinates are given in cm with respect to Spine 1.

Figure 6: Postures (i) and (ii) for Target 6 (-36.5147, 4.23067, 31.9348).

TABLE 6: Performance measures for Target 6, corresponding to the postures shown in Figure 6.

	Effort	Discomfort	Joint Disp.	Pot. Energy	Visual Acuity	Visual Disp.
(i)	4.4619	46.1995	3.4811	2.012	0.8783	0.0357
(ii)	4.5985	52.494	3.6209	2.0103	0.9996	0.0001

Postures and performance measure values for Target 9 are given below. Target 9 is chosen to determine how MOO with additional performance measures effects vision when targets are behind Santos™.

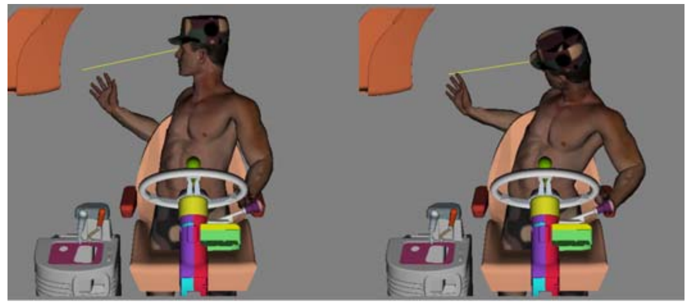

Figure 9: Postures (i) and (ii) for Target 9 (-35, 42,-30).

Performance measures for Target 9, corresponding to the postures shown in Figure 9.

	Effort	Discomfort	Joint Disp.	Pot. Energy	Visual Acuity	Visual Disp.
(i)	21.4364	175.6881	23.5481	10.7724	0.2949	0.3342
(ii)	25.8705	233.0832	26.1257	13.8415	0.9996	0.0001

Analysis of Figure 9 along with the data in Table 9 indicates that introduction of more performance measures as objective functions results in a more life-like posture but greatly affects the accuracy of vision. When vision is used as a constraint, the result is a more uncomfortable posture with a significant increase in visual accuracy; it allows Santos™ to precisely view what he is working with. We can draw the following conclusions based on Test Case #2:

- Using MOO with additional performance measures creates more life-like postures but compromises vision.
- Vision can be used as either an objective function or a constraint when targets are in front of the avatar. There is little difference in predicted postures and performance measure values.
- For tasks that require clear visualization of target points behind the avatar, vision should be used as a constraint as this guarantees that Santos™ will see what he is working with.
- For tasks that do not require visualization of target points behind the avatar, vision may be used as an objective function. This formulation results in more comfortable postures but compromises vision.

CONCLUSION

This study investigates different ways of modeling vision and how it affects predicted posture. The optimization formulations consisted of both single- and multi-objective optimization problems. The first test case was developed in order to isolate the visual displacement performance measure. A small number of objective functions, namely visual displacement and joint displacement, were used. The data from this test case indicated that predicting posture using visual displacement alone does not yield natural postures. When joint displacement was coupled with visual displacement, there was significant improvement in posture realism. However, when the target points were placed outside of the initial viewing space, Santos™ could not see them; the vision vector did not intersect the target point. Using visual displacement as a constraint forced Santos™ to see what he was touching with minimal degradation in the non-vision-based performance measures.

The second test case yielded more realistic postures through the use of additional objective functions. Instead of simply using visual displacement and joint displacement, as in Test Case #1, Test Case #2 involved joint displacement, potential energy, discomfort. Although the realism of the predicted postures increased, the use of additional components in the MOO problem reduced the affect of the vision objective function. However, for certain tasks, humans may simply *try* to look at a target but will not do so at the expense of another performance measures. For these tasks, MOO should be used with a vision objective function

We find that using vision as a constraint provides the same results as using vision as a performance measure when the target is relatively easy to see. Differences in performance between the two approaches come when targets are relatively difficult to see. When modeling human performance, this difference raises the question of when one absolutely has to see a target (possibly at the expense of other criteria) and when one simply makes an effort to see a target. The answer depends on the task being modeled. Certain tasks such as reading a book may not need to be modeled with vision as a constraint as overall comfort is of more importance. Other tasks which require visualization of harder to see targets may best be modeled with vision as a constraint. With the development of this new vision constraint, we are now able to model scenarios when one absolutely must see a target. We can then study the consequences on other types of feedback, such as discomfort.

Typically, with optimization-based methods, constraints are used as boundary conditions that impose restrictions not included in the model. For instance, we do not actually model the complexities of each joint or the complex contact problem involved in bending a joint. Therefore, we apply joint limits as constraints. In a sense, constraints are often used to define the boundaries of the model with respect to fidelity. The objective functions are then used to study what motivates human behavior, given the problem assumptions inherent in the constraints. In the case of vision, when boundary conditions must be imposed depends on the task being modeled.

It is possible to vary Santos's™ anthropometry in order to represent various anthropometric cross sections. Such variation do, in fact result in variability in eth predicted postures. However, with this study, anthropometry was fixed in order to isolate the affects of changes in the performance measure and/or constraints.

One way to improve vision would be to add dynamic eyeballs to Santos. With the target points above where vision performance measures are just slightly less than optimal, eyeball movement could reduce the sight angle (the angle between the vision vector and the target point). Reducing the sight angle would improve the vision performance measures and would likely leave the non-vision-based performance measures unchanged. Additional future work involves optimizing visual displacement with upper limits on non-vision-based performance measures modeled as constraints. As with the development of any predictive model, validation is critical. Basic validation was conducted with the development of the initial performance measures and with posture-prediction capabilities in general (Marler *et al*, 2007; Yang *et al*, 2007). Nonetheless, the validation process is ongoing and will continue. This study involved subjective evaluation of postures, but more objective analyses will be conducted in the future. Finally, as discussed in Marler *et al* (2006), with the development of the vision performance measure used in this work, only one element of vision is considered, albeit the most critical element with respect to posture prediction. Consequently, future work will involve additional components of a complete vision-based model.

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