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Development of a Zone Differentiation Tool for Visualization of Postural Comfort

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ABSTRACT

Over the past several years, significant advances have been made in the area of posture prediction. However, to make simulations more useful for vehicle design, additional unique tools are needed. This research focuses on the development of one such tool, called *zone differentiation*. This new tool allows user to visualize not only the complete reach envelope but also the interior comfort levels of the envelope. It uses a color map to display the relative values of various performance measures (i.e. comfort) at points surrounding an avatar. This is done by leveraging an optimization-based approach to posture prediction. Using this tool, a vehicle designer can visually display the impact that the placement of a control (switch, button, etc.) has on a driver's postural comfort. The comfort values are displayed in a manner similar to how a finite element analysis (FEA) programs display stress and strain results. The development of this tool requires two main components. First, both the simulated postures and the resultant comfort levels are correlated against actual experimental results. Second, the software tools needed to calculate and display the comfort zones, as well as the graphical user interface are developed.

Keywords: Reach envelope, comfort model, zone differentiation, feeling scale.

INTRODUCTION

Reach envelopes are key tools for vehicle interior package design. They provide criteria for the vehicle designer and have been studied extensively for several decades. Despite the usefulness of reach envelopes, they are insufficient, because they do not supply enough information to the designer. Alternatively, *a zone differentiation tool*, such as the one developed in this paper, does more than simply indicate which points are accessible. It actually evaluates the contents of the reach envelope. For every point within the reach envelope, a posture is predicted using a new optimization-based approach such that the virtual human contacts the specified point. The final optimum value for the objective function in that optimization problem provides performance-measure values that correspond to discomfort. Then, we correlate this discomfort to comfort levels. Consequently, a zone differentiation tool provides additional utility for layout design of controls, buttons, etc. Such a tool shows different colors for different comfort levels within the reach envelope. In fact, zone differentiation tools can ultimately present 3D contour plots for a variety of human performance measures such as energy, effort, joint placement, etc. Vehicle designs based on this kind of tool improve comfort and safety.

This paper is an extension of our pilot study on zone differentiation (Yang et al., 2007a, 2007b). We first summarize the optimization-based approach to posture prediction, which is the basis for the zone differentiation tool. This includes the mathematical feeling model used to represent discomfort as a performance measure. Then, we summarize the experimental protocol used to gather actual comfort data in terms of a subjective feeling scale, and we correlate the experimental data with results from the mathematical model. Note that this correlation does not constitute a data-based model; the predicted postures used to analyze the zone do not depend on prerecorded data. Rather, the correlation approach transforms the numerical values of the performance-measure (discomfort) to correspond with a specified pre-existing scale (comfort). Although the general nature of discomfort is modeled mathematically, the actual absolute values and range of a discomfort scale vary from user to user, and we provide a means to accommodate this variability. Finally, we develop a volumetric visualization interface for the comfort level data within the reach envelope. The final zone differentiation tool has three new features. The first feature allows the user to visualize zones gradually from low to high resolution because the data is presented in increasing resolution as it is available. The second feature allows the user to visualize zones interactively via three orthogonal cutting planes. The third feature allows the user to change the transparency of the displayed zones so that the related design surfaces can be seen more clearly.

LITERATURE REVIEW

Based on the initial proposed novel idea about workspace zone differentiation (Yang et al., 2007a, 2007b), this research focuses on the complete package development of zone differentiation tool. However, considerable work has been completed with respect to reach envelopes, which are byproducts of the zones. In addition, an integral component of the zone differentiation tool is the performance measure used to evaluate the points within the reach envelope. Although a variety of measures can be used, in this paper, we focus on one form of comfort. Consequently, in addition to reviewing the state of the art with reach envelopes, an overview of work with comfort/discomfort modeling is provided.

With respect to reach envelope, several approaches have been investigated. The first one is the data-driven method (Hammond and Roe, 1972; Badler, 1997; Chaffin, 2002; Reed et al., 2003; and Parkinson et al., 2003). It need collect thousands of subjects to do the experiment and visualize the collected data in the form of isosurfaces. The second school is the voxel-based method (Troy and Guerin, 2004) and the software was developed. This method includes representing the swept object by voxels, then generating motion voxelization, voxel shell, finally launching tessellation. The third is the closed-form solution (Abdel-Malek et al., 2001; Sharma et al., 2004; Yang et al., 2004a, 2004b; and Yang et al., 2005a, 2005b). This model is limited to six degrees of freedom. The fourth is the probabilistic method (Venema and Hannaford, 2001) but it is also tedious to collect data. Each approach has its pros and cons. The data-driven method is directly from statistical data and is the correct answer. However, it is time-consuming. The voxel-based method is fast, but it can generate holes in the reach envelope. The closed-form method is a general one for all percentiles, but the procedures to determine the singular surfaces are time-consuming. The probabilistic approach represents a statistical model; however, obtaining the answer is also time consuming. In general, the closed-form method can be used to generate reach envelopes of human fingers corresponding to any reference points on human bodies.

Within the human factors/ergonomics community, many researchers have investigated methods to measure or quantify comfort or discomfort, though they define comfort/discomfort differently. The majority of the work that has been completed on comfort and discomfort has been experimental in nature. In addition, the experimental work tends to focus on specific tasks and/or specific body parts (Pan and Schleifer, 1996; Lin et al., 1997; Happee et al., 2000; O'Sullivan and Gallwey, 2005). Cruse et al. (1990) use psychophysical experiments to develop mathematical comfort functions at the wrist, elbow, and shoulder. Their comfort function is in implicit form and depends on the joint angle and the muscle forces necessary to perform a task. The maximum comfort is regarded as the minimum discomfort. The discomfort cost generally takes the form of U-shaped curves depending on joint angles. Jung et al. (1994) provide a normalized joint displacement function as an approximation of joint discomfort. The formulation is based on the idea that discomfort for the arm reaches a minimum approximately when each joint is at its center angle. Jung and Choe (1996) extend this work and use a regression model to create another discomfort function. Zacher and Bubb (2004) propose a discomfort model based on joint angles and forces. They find that discomfort depends on the magnitude and direction of forces at the joints. In addition, discomfort is proportional to how close a joint angle is to its limits, i.e., the degree of flexion. The authors suggest that overall discomfort is highly dependent on the maximum discomfort for a single body part. This suggests that different joints should be viewed independently to some extent. Their discomfort model is a three-dimensional surface function of each joint displacement. Marler et al. (2005) provide a closed form of musculoskeletal discomfort. This model involves three factors: (1) the tendency to gravitate to a reasonably comfortable position, (2) the tendency to move body segments in sequence (i.e., move the arm, then the torso if necessary, and then the clavicle), and (3) the tendency to avoid postures where ligaments and/or tendons are stretched. In this work, we use multiobjective optimization (MOO) to combine the musculoskeletal discomfort (Marler et al. 2005) with a vision performance measure (Marler et al. 2006) and an energy performance measure (Yang et al., 2004b; Marler et al. in press) to yield a general indication of comfort. Based on above different human performance measures we developed a new mathematical feeling model for discomfort, and we refer to this as the MOO function.

MATHEMATICAL FEELING MODEL

The zone differentiation tool is essentially a tool for 1) systematically analyzing a series of points and 2) communicating the results of analysis. This section addresses the method by which the points are analyzed and the mathematical feeling model (MOO function). The following section will discuss how these numerical results are correlated with subjective feeling scale that is dictated by experimentation.

We leverage a new optimization-based approach to posture prediction (Yang *et al*, 2006). The design variables for this problem are joint angles, measured in units of radians. q_i is a joint angle and represents the rotation of a single revolute joint with respect to a local coordinate system. There is one joint angle for each degree of freedom (DOF). $\mathbf{q} = [q_1, \ldots, q_n]^T \in R^n$ is the vector of joint angles in an *n*-DOF model and represents a specific posture. $\mathbf{x}(\mathbf{q}) \in R^3$ is the position vector in Cartesian space that describes the location of the end-effector as a function of the joint angles, with respect to a global coordinate system. For a given set of joint angles $\mathbf{q}$, $\mathbf{x}(\mathbf{q})$ is determined using the Denavit-Hartenberg (DH)-method. The DH-method essentially allows one to work with either joint space or Cartesian space.

With this approach, the constraints are modeled independently. The first fundamental constraint, called the *distance* constraint, requires the end-effector to contact a target point $\mathbf{x}^{target\ point}$. In addition, each joint angle is constrained to lie within predetermined limits. q_i^U represents the upper limit for q_i, and q_i^L represents the lower limit. These limits are derived from anthropometric data. Additional constraints can be used depending on the task being modeled.

The objective function for the optimization formulation is a human performance measure and is a function of the joint angles. Based on the validation study by Marler et al (2007) and Yang et al. 2007), we combine musculoskeletal discomfort (Marler et al., 2005a), visual displacement (Marler et al., 2006), and potential energy (Marler, 2005). These functions are combined using MOO (Yang et al., 2004b; Marler et al., 2005), and the consequent aggregated function represents a new more complete mathematical model of discomfort.

The optimum posture for the human system shown in is then determined by solving the following problem using any number of algorithms for constrained optimization:

$$\begin{aligned} &\text{Find: } \mathbf{q} \in R^{DOF} \qquad (1)\\ &\text{to minimize: Mathematical Feeling Model}(\mathbf{q})\\ &\text{subject to: } \textit{distance} = \left\| \mathbf{x}(\mathbf{q})^{\textit{end-effector}} - \mathbf{x}^{\textit{target point}} \right\| \le \varepsilon \\ &\qquad q_i^L \le q_i \le q_i^U;\ i = 1, 2, \ldots, DOF \end{aligned}$$

where ε is a small positive number that approximates zero.

CORRELATION OF COMFORT MODEL

Given the performance-value results provided by solving (1), we now discuss how these simulation results are correlated with experimental results. The absolute value of feeling model in (1) is not critical; rather, the relative values associated with various target points within the reach envelope are important for evaluating the relative discomfort associated with the different points. Nonetheless, comfort is typically evaluated subjectively, often with respect to a preconceived scale. In addition, the mathematical feeling model refers to discomfort, but the subjective values in the experiment are comfort. Therefore, it is necessary to develop transformation methods such that the performance measure used in this study can be used with any predetermined scale.

SUBJECTIVE FEELING SCALE

A series of motion-capture experiments were run primarily to validate the predictive results from the optimization-based posture-prediction approach, and Yang et al. (2007c) and Marler et al. (2007) detail this validation effort. However, the experimental results also provide significant absolute-values and ranges for a subjective feeling scale.

In the experiments, we have 11 subjects from four different percentiles (AF05, AF50, AM50, and AM95), and each subject is instructed to perform four reaching tasks (Fig. 1). Task 1 requires reaching the point at the top of the A-pillar, which is a relatively simple task. Task 2 requires reaching the radio tuner button, a slightly difficult task. Task 3 requires reaching the glove box handle, and task 4 requires reaching a point on the driver's B-pillar seatbelt adjuster, both of which are slightly more difficult tasks. The average comfort/feeling level for each task was recorded on a scale of 1 to 10, with values greater than 5 indicating an acceptable comfort condition.

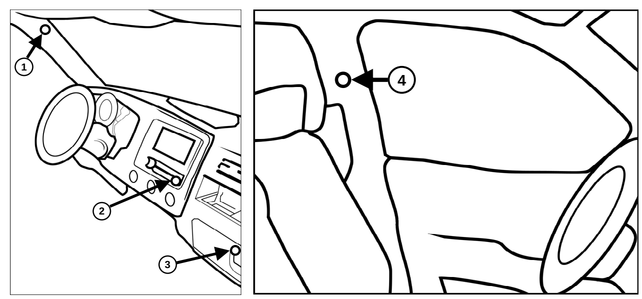


Fig. 1 Four in-vehicle tasks

CORRELATION OF THE MODEL

When solving (1), the assumption is that the absolute values are not significant but that the relative values are important. That means we chose the minimum feeling rating as the upper limit of the MOO function in (1), and the maximum rating as the lower limit of MOO function. These limits are determined analytically. Generally, the values for the mathematical feeling model range between 0 and 2,000 (0 refers to the tasks with the greatest comfort values; 2,000 refers to the tasks with the greatest discomfort values). However, the range of the subjective feeling scale is from 0 to 10 (0 refers to the task with the highest discomfort, 10 to the task with the highest comfort). It is obvious that these two systems are different and that we have to correlate them to make sure the zones generated by the mathematical model are realistic. Fig. 2 demonstrates the differences between the two scales. The mathematical feeling model is non-linear, and the subjective scale is linear.

In the correlation process, we use a *direct mapping method*, which is shown in Table 1. Essentially, simulation values (for the mathematical model) are mapped to specific values for the feeling scale. This mapping can be altered by the user, depending on commonly accepted practices.

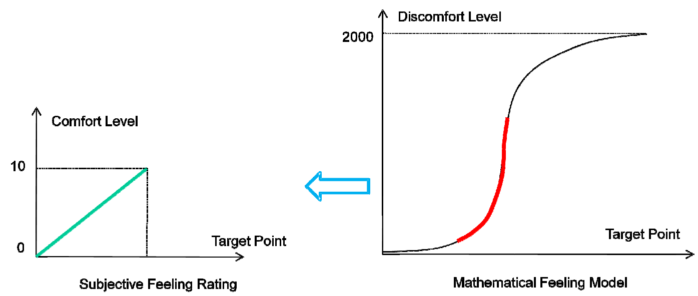


Fig. 2 Transformation from the mathematical model to the subjective feeling scale

There are of course, multiple maps that can be used to transform values for the simulated discomfort to the range of comfort values used in the subjective scale. Consequently, it is necessary to verify that the scheme provides in Table 1 is in fact acceptable. It is necessary to verify that after correlating the two scales, that the simulated discomfort values are desirably mapped to the experimental comfort values.

In order to verify the simulated results, it is necessary to aggregate the experimental data. As indicated, four anthropometric cross sections (percentiles) are considered, and for each percentile, three subjects were used. Thus, the data is evaluated in three forms. First, each individual is evaluated independently, and we refer to this as individual group. Second, the results (comfort values) for each target within one percentile are averaged. This yields four values (one for each target) for each of the four cross sections and is labeled population group. Third, the results (comfort values) for each target are averaged regardless of the percentiles. This results in one value for each target and represents overall group.

R^2 is used as the criterion for the correlation. The regression results are $R^2 = 0.550$ for individual group, $R^2 = 0.841$ for population group, and $R^2 = 0.9761$ for overall group (Figs. 3-5).

In general, the above plots suggest successful correletion between the experimental data and the simulation values. In the individual group case, $R^2 = 0.550$ and is less than 0.7. This can be misleading because experimental data for each participant is more subjective. We should not reply on individual group; instead, we should consider the average of subjects within a percentile, which refers to the population group. R^2 is larger than 0.7 within the population group. This suggests that the mapping rules are reasonable for the four tasks.

Table 1 Mapping rules

Simulation Value	<5.0	5.0~17.0	17.0~40.0	40.0~100.0	>=100.0
Subjective value	9	7.5	6.5	5.5	4.5

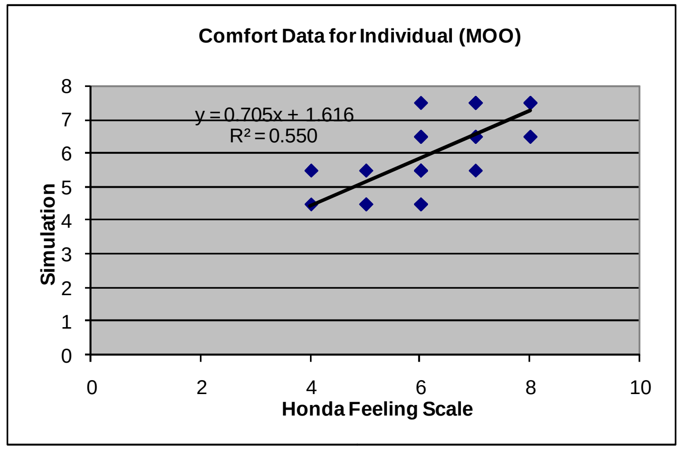


Fig. 3 Correlation results for individual group

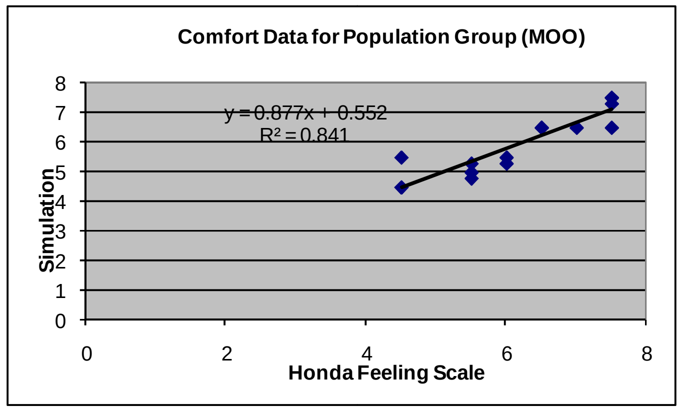


Fig. 4 Correlation results for population group

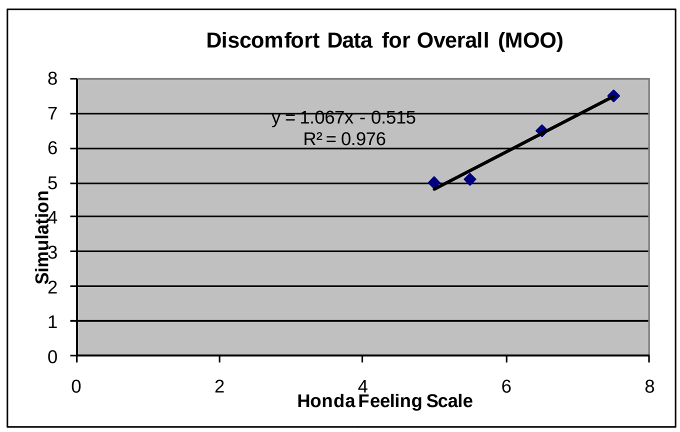


Fig. 5 Correlation results for overall group

ZONE DIFFERENTIATION TOOL

The zone differentiation tool is a tool for visualizing zones with different human performance measures or a combination of them in 3D space around a subject. Zone differentiation can determine how effectively a subject reaches space around him/her. This is a useful tool in the analysis of designs that involve user interaction. The users first choose a reference point for the subject—for example, the waist or shoulder. Then, the user selects the human performance measures or a combination of them, a resolution in which to show the zones, the number of colors for the zones, and the types of colors. The user can visualize zones in different colors that correspond to comfort levels. In this section, we present the structural components of the zone differentiation software and the capabilities and features of the zone differentiation tool.

The zone differentiation (ZD) software tool involves a collection of smaller components working together. Fig. 6 shows the flowchart of zone differentiation. The following list briefly explains several components presently in use within our zone differentiation system:

(1) Posture prediction. Posture prediction is the main component of the zone differentiation tool and computes performance measure values while predicting realistic human postures using an optimization-based approach.
(2) LibZone library. LibZone library is another major component of the zone differentiation tool. It primarily transforms performance measure values into visual information.
(3) ZD shared library. This is a shared library used by both LibZone and the Virtools zone differentiation building block to communicate with each other, where Virtools provides a real-time interactive environment with superior graphics and complex interactivity. This library is implemented as a standard *Win32 Dynamic Link Library.*
(4) ZD building block. This Virtools building block works as an interface between the combined unit of posture prediction and LibZone, which collectively generates numerical values and computes visualization information, and Virtools, which presents the information in visual form to the user.

ZD parameters building block. This Virtools building block is similar to the ZD building block, but it performs more user- and display-centric processes such as allowing the user to change the transparency of zone differentiation visualization or apply user-specified color profiles to zone differentiation visualization. To represent spacial information around a subject, ZD employs 3D volume textures. A 3D texture is similar to a 2D array of pixels except with a third dimension. A 2D texture is essentially represented as a 2D array of pixels. Similarly, a 3D texture is an array of 2D textures or a 3D array of voxels. Voxels in this 3D texture are mapped to the units of space around a subject. These units are arbitrary and are the same units used to represent link lengths of body segments in the posture prediction. For example, a length of 5 cm along a certain axis can be represented as 5 voxels on the same axis. The center of the 3D volume texture is made to coincide with the origin of the subject. Since locations within a 3D texture are represented only on the positive axis, we need to transform the center of the volume texture to the origin of the subject. For example, to store the value of a human performance measure at location (x, y, z) in the subject 3D space, we go to location $(x_c + x, y_c + y, z_c + z)$ within the texture and store the human performance measure value. (x_c, y_c, z_c) represents the center of the volume texture, and $x_c=y_c=z_c$=resolution/2. This way, a 256^3 texture can be used to represent points in a space that extends 128 units in each direction on each of the three axes.

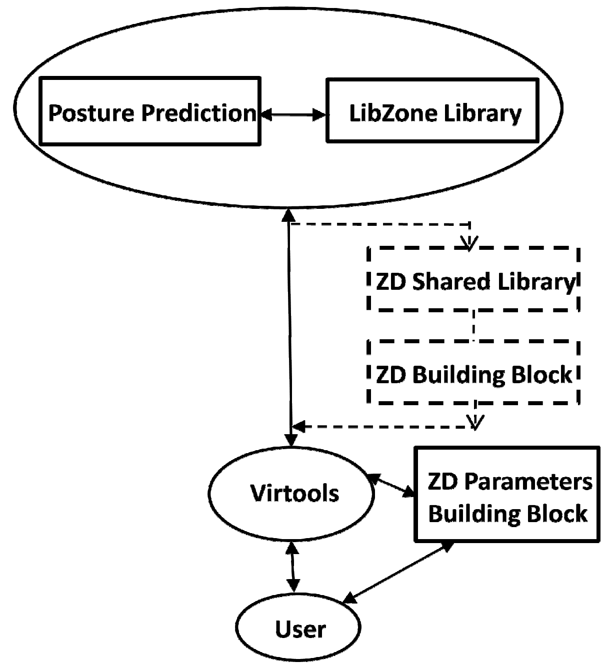


Fig. 6 Components of zone differentiation

Posture prediction then computes the performance-measure values at the coordinate locations of each of the voxels in this 3D texture. The LibZone module places the computed performance-measure values at the appropriate locations within this 3D texture. While this calculation proceeds, LibZone keeps updating the shared data blocks in the ZD shared library so that they become available to external components like the ZD building block.

We use a 32-bit floating point texture to store values in our 3D texture. This texture format is not directly displayable on screen; therefore, a hardware shader is used to convert floating point information into colors. This format for textures provides us with the flexibility of storing high-precision results in our 3D textures. Also, it enables us to make the coloring process completely confined within the hardware shader.

The information stored in shared blocks by LibZone during the computation process is used by the ZD building block to provide feedback to the user. This building block provides information such as the total number of points to be computed, the total number of points completed, the estimated time left, and various other such values. Since the zone differentiation process takes several days to complete, it is critical to present this information to the user.

Finally, the ZD parameters building block allows the user to control how the data visualization is performed in two ways. First, it generates the hardware shader used to render the visualization based on the colors chosen by the user, also called the color profiles. Second, it allows the user to change the transparency of the visualization so that the user can see inside the volume.

The computation process can take a long time to finish. Therefore, we devised an approach that allows the user to monitor the progress visually. We compute a series of textures, each increasing in resolution from the last by a power of two. This is done essentially to provide the user with appropriate feedback considering the amount of time it will take to complete the zone differentiation calculations.

Note that the user has the flexibility to specify a target resolution for the visualization. In other words, if the user thinks that it might take a long time to compute a zone differentiation computation to the finest level of detail, and such fidelity is not necessary for the task at hand, then the user can specify a relatively low target resolution for the visualization. As soon as the computation reaches this target resolution, the computations stop. For instance, if the user thinks that a 32^3 volume provides enough detail, the user can specify 32 as the target resolution. The computation will stop as soon as the computation process gets done with the 32^3 texture.

EXAMPLES

In this section, we demonstrate the zone differentiation tool using a single subject. This tool has several features. First, the user can run the tool to visualize zones from low to high resolution rather than waiting for all the final data to be available. As described in the section above, running the posture prediction for the whole workspace with a high resolution (256^3) takes more than one day. To avoid having the user wait for the final zones while nothing comes out for a long time, we developed this functionality so the user can visualize the raw results from the beginning and then gradually, as more target points are added, visualize the progress and more accurate results. The second feature is that the user can slide the three orthogonal cutting planes through the workspace intuitively. The third feature is that the user can change the transparency of the zones using the slider bar.

Figs. 7 through 12 show snapshots of zones gradually changing with the increased resolutions.

Fig. 13 shows the zones with different cross section positions of the first sliding plane within the workspace. Similarly, we can slide other cutting planes to visualize zones in Figs. 14 and 15.

Fig. 16 shows the transparent zones by an interactive slider bar. This feature is useful when the user uses the tool in the crowded environment of the product design.

Fig. 7 Resolution with 4x4x4

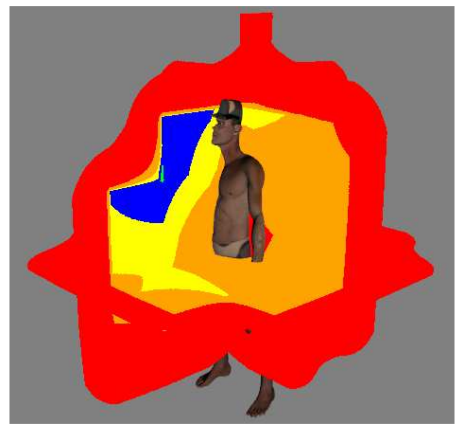


Fig. 8 Resolution with 8x8x8

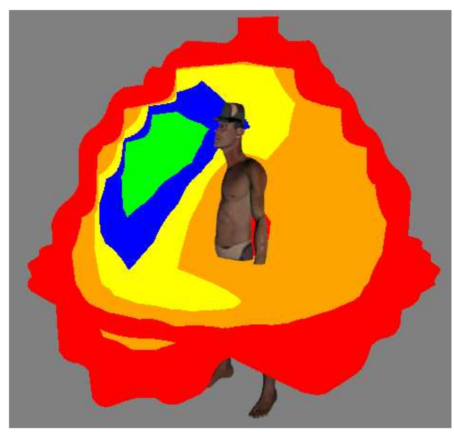


Fig. 9 Resolution with 16x16x16

Fig. 10 Resolution with 32x32x32

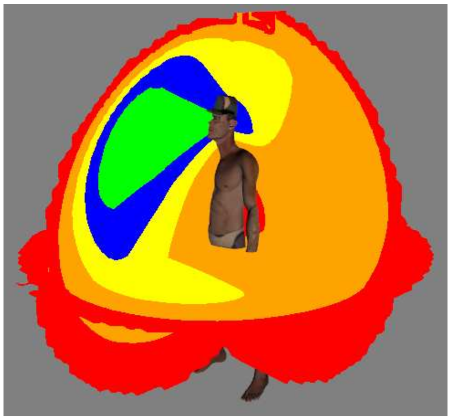


Fig. 11 Resolution with 64x64x64

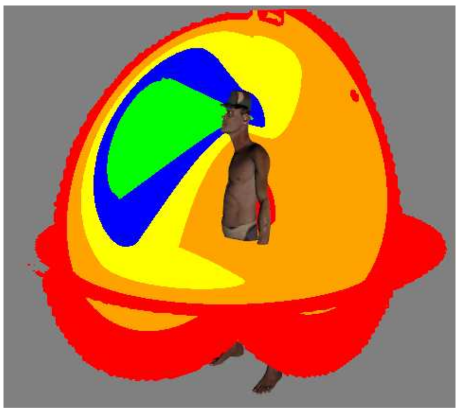
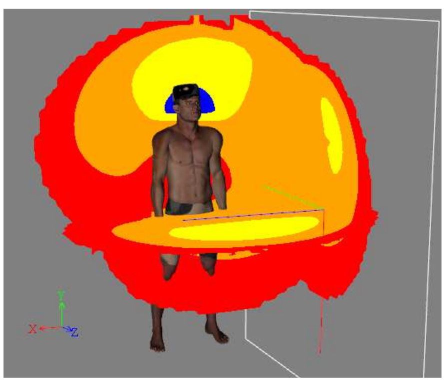
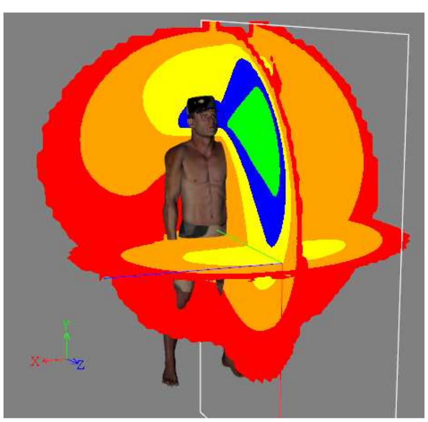


Fig. 12 Resolution with 128x128x128





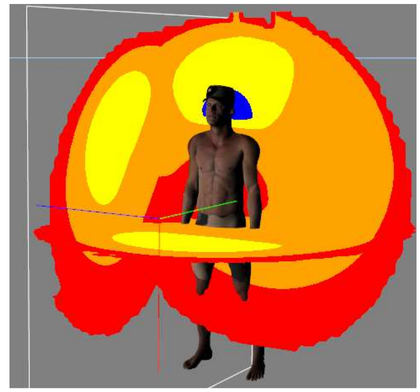
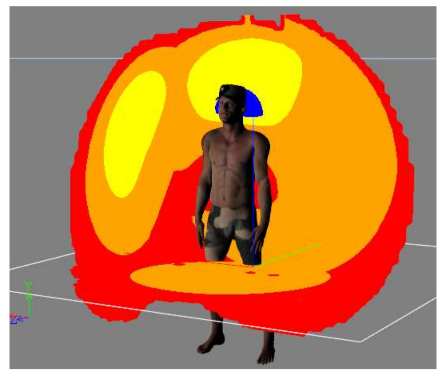
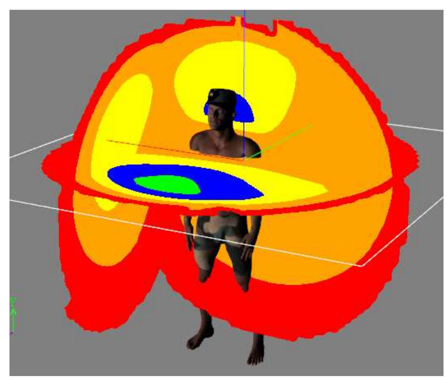


Fig. 13 Resolution with 128x128x128 with the cutting plane 1 in a new position





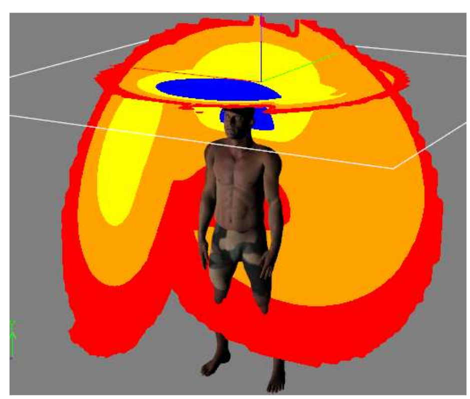


Fig. 14 Resolution with 128x128x128 with the cutting plane 2 in a new position

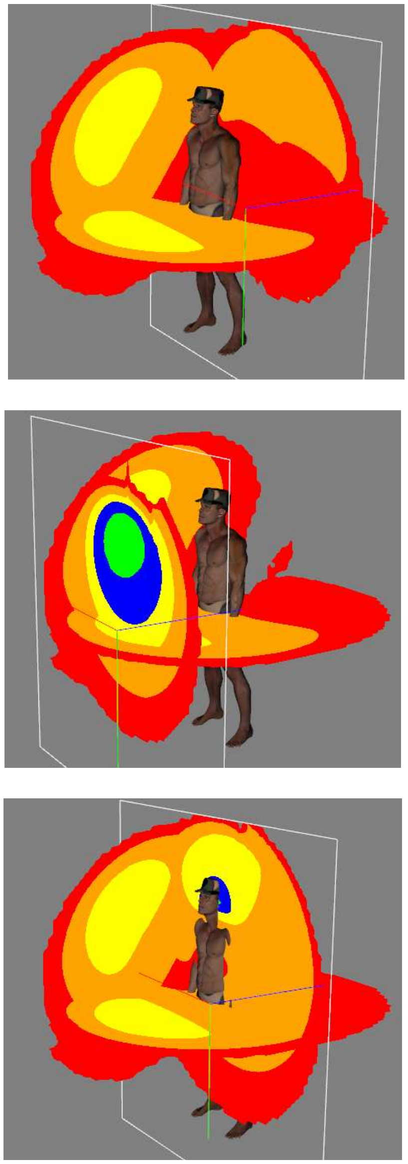


Fig. 15 Resolution with 128x128x128 with the cutting plane 3 in a new position

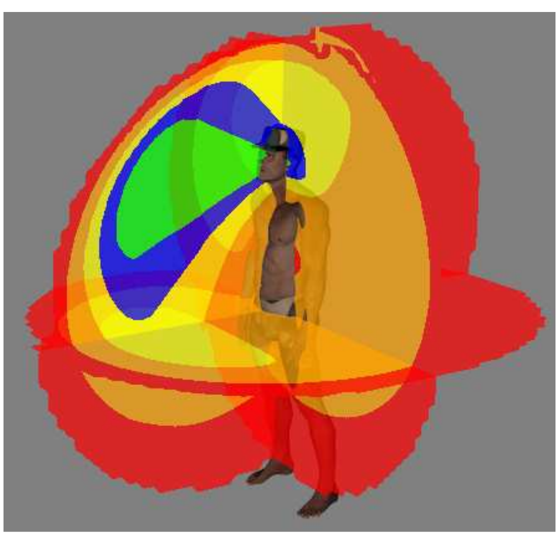


Fig. 16 Zones with transparency

CONCLUSION

The primary contribution of this work has been the development of a new zone differentiation tool that leverages a novel approach to posture prediction and extends the current applications for common reach envelopes. This development involves efficient methods for handling extremely large sets of data. It also involves elegant methods for communicating the results of complex analysis. The result is a unique tool for product design and layout design. The user can not only choose different colors for the zones, but can also use different levels of transparency to visualize the zones. This tool has two important features: the ability to vary resolution and the ability to move cutting planes. In general, this real-time tool provides significant momentum for human centric design in a variety of fields.

In developing this tool, we have also presented a direct mapping method for correlating feeling scales. We have shown that a mathematical feeling model can be accurately transformed to a subjective feeling rating. However, we find that one should not use the individual group to judge the correlation efficiency, because the comfort levels are subjective for individuals. Rather, one should average the values within a percentile. The population group is the correct one to use to evaluate the correlation results.

Developing a means of correlating analytical results with current evaluation methods (subjective feeling scales) raises an interesting issue with regards to evaluating comfort. The components of the mathematical model are physically significant derived from biomechanical concepts. The primary intent of this model is to predict human posture accurately, when the model is implemented in (1). As suggested, the absolutely values of the objective function in (1) are irrelevant with regards to this intent. However, when posture prediction is used in the context of zone differentiation, one must consider the ultimate application. Ultimately, a designer will need specific cut-off values for analysis, indicating, for example where a control can be placed without being too uncomfortable. These values may be specified by the user/designer, or they maybe stipulated based on policies or past experience. In either case, these cut-off values are presumably related to the impressions of a customer, someone that uses the product being designed. However, while the trends in perceived discomfort can be similar for a customer as they are for the mathematical model, the absolute values (and thus the cut-off values) depend heavily on a basis for comparison. That is to say discomfort is always relative. When the mathematical model is used with a virtual human to evaluate different targets, discomfort values are determined relative to the maximum possible value of the objective function in (1). This maximum value is based on a sound biomechanical model. However, when a customer indicates the relative discomfort of different targets, it is difficult if not impossible to tell what the basis of comparison is. One person may rate the discomfort of various targets based on the target that is most uncomfortable to touch, while another customer may rate comfort based on some unknown extreme condition (i.e. a past injury). Consequently, basing designs on subjective data can be difficult and risky. A sound mathematical biomechanical model, such as the one used for this study, provides a more consistent means for human centric design.

Based on the features of this tool, a variety of potential areas for future work have surfaced. The tool should be extended to allow the user to: (1) visualize other human performance measures such as joint displacement, delta potential energy, and visual displacement, (2) move a previously generated zone differentiation envelope around in space and intersect it with existing design surfaces to see whether the designed surfaces work out, (3) choose a reference point on the body and visualize the zone differentiation from the end-effector (e.g., hand) to that reference point, and (4) visualize zone differentiation for other limbs such as legs and fingers.

Research is ongoing to consider more parameters within the mathematical feeling model, such as joint torques. The ultimate goal is to develop an accurate and complete package to visualize the zone differentiation of humans based on postural comfort.

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