How sports behavior uncertainty affects player’s visual comfort in national fitness halls: A probabilistic assessment approach

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Abstract

Most visual comfort assessment methods rely on glare analysis in few representative and fixed view scenes, while sports spaces yield challenges given player’s continuously-changing view positions and directions in sports-related visual tasks. Existing simulation tools mostly fail to deal with sports behavior uncertainty. This study develops a probabilistic visual comfort assessment approach for national fitness halls by better quantifying sports behavior uncertainty in glare simulation. We conducted a case study with a prototype national fitness hall model and ran glare simulations under two typical sports scenarios (i.e., tennis, basketball) to demonstrate how sports behavior uncertainty affects player’s visual comfort. The results indicate that sports behavior uncertainty can lead to a discrepancy by 4.0% and 11.8% between deterministic and probabilistic visual comfort under tennis and basketball scenarios. Furthermore, the discrepancy is susceptible to the court location within the large sports space. This study reveals that neglecting the impact of sports behavior uncertainty can result in a considerable error in the visual comfort assessment under sports scenarios.

Highlights

- Sports behavior uncertainty is quantified in visual comfort assessment of national fitness halls.
- Glare simulation model is coupled with the probabilistic behavior model for more realistic and realiable visual comfort assessment.
- Discrepancies between detemrministic and probabilistic visual comfort are observed up to 4.0% and 11.8% under tennis and basketball scenarios.
- The player’s visual comfort is highly affected by sports behaviors uncertainty within national fitness halls.
- The impact of sports behavior uncertainty on visual comfort is vulnerable to the court location within the large sports space.

Practical Implications

The paper introduces a detailed path of how practitioners can couple sports behavior modelling with visual comfort assessment in large sports spaces (such as national fitness halls, NFH), and how to map the glare-risk view scenes in large sports spaces under various sports scenarios, thus providing designers and facility management personnel with effective suggestions on court location arrangement.

Introduction

Occupant behavior is one of the major contributors to the uncertainty in building energy and comfort performance simulation (Malik, Mahdavi et al. 2022), which is not well understood and is often oversimplified in building performance simulation (Muron, Gaetani et al. 2019). The incorrect representation of occupant behavior can however result in the performance gaps between simulated models and actual situations (Hong, Yan et al. 2017, Malik, Mahdavi et al. 2022).

The research community has been working for developing and implementing robust and fit-for-purpose occupant behavior models (Gaetani 2019) into building energy and comfort performance simulations. Hong et al. (Hong, Yan et al. 2017) presented ten questions concerning concepts, applications, and methodologies in occupant behavior research. Gaetani et al. (Gaetani, Hoes et al. 2020) introduced a holistic approach for appropriate occupant behavior modelling in building performance simulation. Kang et al. (Kang, Yi et al. 2022) presented a general framework of modelling occupants’ horizontal and vertical movements in buildings using IVE experimental platform, which can create realistic agent-based models (ABMs) for simulation. Danell et al. developed a simulation workflow to evaluate the non-visual effects of lighting, in which four typical user profiles in a side-lit office were considered. Despite the improved understanding of occupant behavior and achieved modelling approaches, appropriate quantification of certain occupant behavior aspects for specific performance simulation purposes still requires high computational cost (Cali, Mueller et al. 2019) and abundant user data (Danell, Ámundadóttir et al. 2020) which is often unavailable. Within the scope of this study, the research community has not yet achieved a generic framework to model sports behavior in visual comfort assessment.

Quantifying sports behavior uncertainty within the glare simulation framework for more realistic and realiable visual comfort assessment still remains a challenge. Unlike normal occupant behaviors with stable and consistent visual tasks (such as workers in offices), sports behavior is more complex and dynamic which yields continuously-changing view scenes across the sports space, the spatial locations and possible view directions...
of players are difficult to predict. In this study, we investigate how the integration of sports behavior uncertainty into glare simulation impacts the visual comfort assessment results, and therefore trying to answer the following research questions:

- How to appropriately model player’s sports behavior and consider its uncertainty within annual glare simulation?
- How does sports behavior uncertainty affect player’s visual comfort under tennis and basketball scenarios?

**Methods**

The research framework is elaborated in Figure 1. Firstly, annual glare simulation model was established based on a prototype national fitness hall using Rhinoceros & Grasshopper and ClimateStudio, relevant simulation settings were then prepared. Besides, established view scenes in glare simulation were carefully set up. Secondly, the probabilistic behavior model was constructed to quantify player’s occupancy probability in all possible view scenes, by combining the player-tracking data with a developed probability-based model. Meanwhile, the deterministic behavior model was established assuming that players would equally locate at each view position, and identically experience each view direction. Finally, the deterministic and probabilistic behavior models were coupled with annual glare simulation model to calculate the deterministic and probabilistic visual comfort, which were compared to investigate the impact of sports behavior uncertainty on visual comfort. To facilitate the proposed framework, an integrated computational workflow was established using Rhinoceros & Grasshopper and ClimateStudio, as shown in Figure 2. The next subsections will detail each part.

**Annual glare simulation model**

- **Prototype national fitness hall model**

To set up the annual glare simulation model, we first establish a prototype national fitness hall (NFH) model based on the field survey of more than 50 typical NFHs in China. As shown in Figure 3(a), the prototype NFH model consists of two large sports halls and four-storey accessory spaces, with the dimension of 75m (length) * 55m (width) * 24m (height), the second-floor sports space in dimension of 60m (length) * 40m (width) * 24m (height) is selected as the target area in this study. 11 skylights are built in the NFH model to provide top daylighting for the targeted sports space. The dimensions of the prototype NFH model is summarized in Table 1. Given the fact that side blinds are kept down to prevent discomfort glare during sports, the side windows are not considered in this study. Moreover, this study only investigates the daylight visual comfort, artificial lighting is not considered for this case study.

Since there are various types of sports in NFH, for simplification, two typical sports scenarios are considered, i.e., tennis and basketball. As shown in Figure 3(b-c), the court location within the target area is defined by the court starting point (P0, top left corner of player’s occupied area) and court domain (standard tennis and basketball court), given the buffer distance between the court domain and the boundary of player’s occupied area, all possible court locations within the targeted sports space can be determined: under tennis scenario, P0 ∈ [0, 275]; under basketball scenario, P0 ∈ [0, 539].

**Table 1: Dimensions of the prototype NFH model.**

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Dimension</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
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<td>m</td>
</tr>
<tr>
<td></td>
<td>Width</td>
<td>55</td>
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<td>Floor height</td>
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<td>Target area</td>
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<tr>
<td></td>
<td>Width</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>Floor height</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>Skylights</td>
<td>Skylight number</td>
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<td>-</td>
</tr>
<tr>
<td></td>
<td>Skylight length</td>
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<td>m</td>
</tr>
<tr>
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<td></td>
</tr>
<tr>
<td></td>
<td>Skylight height</td>
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<td></td>
</tr>
<tr>
<td>Shades</td>
<td>Louver depth</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Louver spacing</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Louver unit rotation angle</td>
<td>5</td>
<td>°</td>
</tr>
</tbody>
</table>

- **Weather data/City**

The case study was carried out using the prototype NFH model in Shenzhen, China. The Typical Meteorological Year (TMY) weather data was used to acquire the climate data of Shenzhen, China.

- **Established view scenes**

The whole player’s occupied area is separated into multiple regions with a grid size of 1m, the center of each region is defined as the view position (VP), each with 24 established view directions (rotation angle is 15°) in a vertical eye height of 1.5m. Hence, for glare simulation under tennis scenario, there are totally 11424 established view scenes at 476 view positions (see Fig. 4); For basketball scenario, there are 10080 established view scenes at 420 view positions (see Fig. 5).

- **Simulation setup**

The detailed simulation settings are concluded in Table 2.

**Table 2: Simulation settings.**

<table>
<thead>
<tr>
<th>Run parameters</th>
<th>Sensor grids</th>
<th>Layer materials</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run type: Annual Glare</td>
<td>Sensor spacing: 1m</td>
<td>Eaves: R.vis: 49.8%</td>
</tr>
<tr>
<td>Ambient Samples: 4096</td>
<td>Target Inset: 1m</td>
<td>Interior Walls: R.vis: 50% Exterior Walls: R.vis: 38%</td>
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<td>Ambient Bounces: 6</td>
<td>View plane offset: 1.5m</td>
<td>Ceiling: R.vis: 70%</td>
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<td>Weight Limit: 0.01</td>
<td>Occupancy schedule: 8am-6pm with DST</td>
<td>Floors: R.vis: 20%</td>
</tr>
<tr>
<td>Save hourly data: Yes</td>
<td>View directions: 24</td>
<td>Windows: R.vis: 13.5%; T.vis: 80.4%</td>
</tr>
</tbody>
</table>

- **Probabilistic behavior model**

Within the same target area (2nd-floor sports space), two typical sports scenarios (i.e., tennis and basketball) are considered in visual comfort assessment in this work. To
quantify player’s sports behavior uncertainty, we develop the probabilistic behavior model for each sport scenario based on player-tracking data, which can be used to predict player’s occupancy probability in all possible view scenes, $V_{(i,j)}(VP_i,VD_j)$. The probabilistic behavior model consists of three parts: 1) Extract online realistic player-tracking data to calculate player’s occupancy probability at all view positions ($VP_i$), denoted as $OP_i$; 2) Develop a probability-based model to predict player’s occupancy probability in all possible view directions ($VD_j$), denoted as $OP_j$; 3) Combine $OP_i$ and $OP_j$ to quantify player’s occupancy probability in $V_{(i,j)}$, denoted as $OP_{(i,j)}$.
• Scenario 1: Tennis

A tennis match data of Australian Open Mens’s Final 2019 (Seidl 2019) was used as the reference player-tracking data. To quantify player’s occupancy probability at each view position ($OP_i$), we assume that player’s spatial positions within region $i$ are regarded at $VP_i$, $i \in [0, 0.475]$, as shown in Figure 4(a). Hence, $OP_i$ can be calculated as Eq. (1).

$$OP_i = \frac{\text{Occur}(VP_i)}{M}$$  \hspace{1cm} (1)

Where: $\text{Occur}(VP_i)$ denotes the occurrences of player’s spatial location at $VP_i$, and $M$ denotes the number of total player’s locations throughout the half-court, both are counted from the selected player-tracking dataset.

To predict player’s occupancy probability in all possible view directions ($OP_i$), a probability-based model was developed, as shown in Figure 4(b). In this model, two tennis players (A & B) fight with each other locating at two-half courts. Assume that Player A’s view positions on the left half-court are the starting-points, represented as $VP_i$, all possible objective-points from $VP_i$ are defined as view positions within the same half-court, denoted by $VP'_i$. Let $VD_p(i)$ represent all possible view directions at $VP_i$, i.e., the connection between $VP_i$ and $VP'_i$. Let $VD_e(j)$ represent the established view directions within annual glare simulation ($j \in [0, 23]$). Hence, any two adjacent established view directions can be denoted as $VD_e(j)$ and $VD_e(j+1)$ (0°~15°), let $\alpha$ represent the included angle between $VD_p(i)$ and $VD_e(j)$. For any $VD_p(i)$, when $\alpha \leq 0.5 \times 0\degree$, the $VD_p(i)$ is approximately regarded as $VD_e(j)$, otherwise, $VD_e(j+1)$, as shown in Figure 4(b). The player’s occupancy probability in each view direction ($OP_i$) could be calculated as Eq. (2).

$$OP_j = \frac{\text{Occur}(VD_j)}{N}$$  \hspace{1cm} (2)

Where: $\text{Occur}(VD_j)$ denotes the occurrences of player’s view direction in $VD_j$, calculated by the developed probability-based model; $N$ denotes the number of total possible view directions at $VP_i$ ($N = 96$). By combing the $OP_i$ and $OP_j$, player’s occupancy probability in each view scene ($OP_{(i,j)}$) could be calculated as Eq. (3).

$$OP_{(i,j)} = OP_i \times OP_j$$  \hspace{1cm} (3)

• Scenario 2: Basketball

A detailed basketball shot chart data of NBA 2018-2019 (Teo 2020) was used as the reference player-tracking data. Similarly, to quantify player’s occupancy probability at each view position ($OP_i$), we assume that player’s spatial positions within region $i$ are regarded at $VP_i$, $i \in [0, 0.419]$, as shown in Figure 5(a). Thus, $OP_i$ can be calculated by Eq. (1).

To predict player’s occupancy probability in all possible view directions ($OP_i$), a probability-based model was developed, as shown in Fig. 5(b). In this simplified model, only the shooting directions of the basketball player from all possible regions is the focus of this study (Shi, Zhang et al. 2021). Suppose that player’s view positions on the left half-court are the starting-points, represented by $VP_i$, the objective-point is exactly where the basket is located, denoted by $VP'_i$. Let $VD_{shot}$ represent the shooting direction at $VP_i$, i.e., the connection between $VP_i$ and $VP'_i$, as illustrated in Figure 5(b). Similarly, $OP_i$ can be calculated by Eq(2) saying that the only one $VD_{shot}$ is taken as $VD_p(i)$. Therefore, $OP_{(i,j)}$ could be calculated by Eq(3).
Figure 4: (a) Tennis player’s spatial positions within each region of the occupied area; (b) All possible view directions from a given view position in tennis.

Figure 5: (a) Basketball player’s spatial positions within each region of the occupied area; (b) The shooting directions from a given view position in basketball.
Deterministic and probabilistic visual comfort calculation

Discomfort Glare Frequency (DGF) has been utilized to evaluate annual visual comfort, which denotes to the annual occurrences exceeding the DGF limit (0.38) at a given view scene (Jones 2019). Correspondingly, Spatial Discomfort Glare (sDG) is employed to evaluate the overall visual comfort of a space which denotes to the fraction of view scenes in a space that report discomfort glare exceeding a temporal fraction threshold of 5% of annual occupied hours (De Luca, Sepúlveda et al. 2022).

Assume that DGF at VP with VDj is DGF(i,j), i ∈ [0, m], j ∈ [0, n], then DGF(i,j) and sDG could be formulated by Eqs. (4-5):

\[
\begin{align*}
DGF(i,j) &= \frac{\sum_{k=1}^{3650} w_k(i,j) \cdot t_k(i,j)}{\sum_{k=1}^{3650} t_k(i,j)} \\
sDG &= \frac{\sum_{j=1}^{n} S(i,j)}{\sum_{j=1}^{n} S(i,j)} \text{ where: } t_k = \begin{cases} 
1 & \text{if } DGP(k,i,j) \geq DGP_{\text{limit}} \\
0 & \text{if } DGP(k,i,j) < DGP_{\text{limit}}
\end{cases}
\end{align*}
\]

where: \( t_k \) is the occupied hour of a year (Duration of 10 hours every day for 365 days, from 8:00 am to 6:00 pm); \( w_k(i,j) \) is a weighting factor (0 or 1) that depends on \( DGP(k,i,j) \) and \( DGP_{\text{limit}} \), which represent the DGP of a given view scene \( V(i,j) \) in hour \( t_k \) and the DGP limit (0.38), respectively; \( \sigma \) is the temporal fraction threshold (BSI 2018); \( m+1 \) is the number of total established view positions in tennis or basketball court; \( n+1 \) is the number of total established view directions at each view position.

To integrate sports behavior uncertainty into visual comfort assessment, we defined the ‘Probabilistic Visual Comfort’ (VCP) as a new metric to evaluate the possibility of player’s reporting visual comfort during sports. To be specific, the player’s occupancy probability in \( V(i,j) \), i.e., OP(i,j), is integrated with the glare performance in the corresponding \( V(i,j) \), i.e., DGF(i,j). Meanwhile, the ‘Deterministic Visual Comfort’ (VCD) was defined as the baseline assuming that players would equally locate at each view position, and identically experience each view direction, namely, \( OP^d = \frac{1}{0.5 \cdot (m+1) \cdot (n+1)} \), calculation of deterministic and probabilistic visual comfort refer to Eqs. (6-10):

\[
\begin{align*}
DGF_d(i,j) &= DGF(i,j) \cdot OP_d^d \\
sDG_d &= \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} DGF_d(i,j) \cdot G_d(i,j)}{\sum_{i=1}^{m} \sum_{j=1}^{n} G_d(i,j)} \\
DGF_p(i,j) &= DGF(i,j) \cdot OP_p^d \\
sDG_p &= \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} DGF_p(i,j) \cdot G_p(i,j)}{\sum_{i=1}^{m} \sum_{j=1}^{n} G_p(i,j)}
\end{align*}
\]

\[
\begin{align*}
\sigma_d &= \sigma_d = \frac{1}{(m+1) \cdot (n+1)} \times \sigma \quad (\sigma = 5\%) 
\end{align*}
\]

Where: \( \sigma_d \) and \( \sigma_p \) are annual temporal fraction thresholds of \( DGF_d(i,j) \) and \( DGF_p(i,j) \).

Results and Discussion

Impact of sports behavior uncertainty on visual comfort

To investigate how sports behavior uncertainty impacts player’s visual comfort under various sports scenarios, comparison of sDGd and sDGp under tennis and basketball sports were conducted, as shown in Figure 6. It can be drawn that by considering player’s occupancy probability in all view scenes, remarkable discrepancy between sDGd and sDGp is observed, which is vulnerable to the court location (P0) within the targeted sports space. Furthermore, the overall trend of court location’s influence on visual comfort is similar between tennis and basketball sports, the turning-point of P0(Tennis) = 116 and P0(Basketball) = 326 for tennis and basketball can be witnessed when the gap between sDGd and sDGp is the smallest.

The fluctuation of sDGp with the change of P0 is much smaller than that of sDGd, indicating that player’s occupancy uncertainty has great influence on the player’s visual comfort. Moreover, sports behavior uncertainty can affect player’s visual comfort differentially under two sports scenarios, which can be inferred by the gaps between sDGd and sDGp in Figure 6(a-b). Compared with tennis, basketball player’s occupancy probability can affect visual comfort to a greater extent, which can be explained by the fact that basketball players share a wider range of view directions during sports than tennis players.

Figure 6: Comparison of deterministic and probabilistic visual comfort. (a) Tennis; (b) Basketball.
Absolute deviation between deterministic and probabilistic visual comfort

To more intuitively understand the impact of sports behavior on visual comfort, we calculated the absolute deviation between $sDG_d$ and $sDG_p$ under tennis and basketball scenarios. A mean absolute deviation of 0.018 and 0.04 across all court locations are observed for tennis and basketball, respectively. Besides, it can be concluded that for tennis sport, when $P_{0|Tennis} \in [0, 275]$, the absolute deviation between $sDG_d$ and $sDG_p$ varies significantly with the change of $P_{0|Tennis}$: While for basketball sport, when $P_{0|Basketball} \in [0, 326]$, obvious fluctuation of the absolute deviation between $sDG_d$ and $sDG_p$ can be witnessed, while when $P_{0|Basketball} \in (326, 539]$, the fluctuation amplitude is inconspicuous.

From Figure 8(b) and Figure 5(a), it can be drawn that for basketball sport, player’s locations near three-point line need to be carefully focused.

By mapping those glare-risk view scenes, we can provide designers with evident suggestions on court layout arrangement, meanwhile, necessary shading control strategies need to be adopted to avoid uncontrollable glare.

Figure 7: Absolute deviation between deterministic and probabilistic visual comfort. (a) Tennis; (b) Basketball.

Mapping of glare-risk view scenes

To translate the simulation results into more informed design guidance, we mapped the glare-risk view scenes that request more attention from designers and facility management personnels. Under tennis (basketball) scenarios, according to Eq. (10), those view scenes with $DGF_{p(i,j)}$ larger than 8.75e-6 (9.92e-6) are considered as glare-risk view scenes that are mapped in red colors, as depicted in Figure 8.

Moreover, our proposed approach helps to identify the critical view scenes of undertaking glare risks by players during tennis and basketball sports. By mapping the glare-risk view scenes to the specific court location within the large sports space, detailed court arrangement recommendations can be provided to designers and facility management personnels to minimize the negative effects of discomfort glare, and to develop effective mitigation measures for avoiding possible disturbing impacts. Furthermore, this study contributes a generic methodological framework of integrating sports behavior modelling into visual comfort assessment which can be transferred to similar sports and spaces. Given the complexities and differences of various sports types, future work will consider agent-based modelling (ABM) approaches to generate user profiles in the absence of recorded sports behavior data, especially at early design stages.

Conclusion

This study provides a better understanding of how sports behavior uncertainty affects player’s visual comfort in national fitness halls, and clarifies the advantages of assessing visual comfort with sports behavior considerations by coupling the glare simulation model with the developed probabilistic behavior model. Through this study, we can more intuitively understand the impact of sports behavior on visual comfort, especially at early design stages.
Acknowledgement

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References


