User-specific predictive affective modeling for enclosure analysis and design assistance

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Abstract: There have been multiple recent lines of quantitative inquiry into the correlations between spatial parameters of virtual enclosures, and the corresponding emotional responses in occupants. The application of such empirical approaches for occupant-specific predictive affective modeling and design assistance is, however, a very nascent domain. This paper outlines a design assistance workflow for rapid user-specific data collection and predictive affective analysis of enclosures in early stage design. For demonstration, 100 enclosures randomly generated along 9 spatial parameters – length, width, ceiling height, sill height, lintel height, no of windows, window position, total window width and wall hue – were presented to 5 subjects through cursor controlled displays as well as immersive VR environments, and were subsequently rated on an EmojiGrid, based upon the Circumplex Model of Affect. For design assistance, the framework allowed the designer to import any subject-specific dataset, and then applied K-Nearest Neighbour (KNN) regression algorithms to evaluate the affective impact of a designed test enclosure in real time, based on its spatial parameters and subject-specific training data. This research thus aims to integrate 'subjective' patterns of affective response into a computational framework, and open up possibilities for the 'emotional customization' of spaces.

Keywords: Affective Customization; Enclosure Analysis; Machine Learning; Design Assistance.

1. Introduction and Background

The emotional or 'affective' qualities of space have long been referred to as 'intangible' aspects that cannot easily be empirically analyzed or evaluated. The sensorial, experiential, and emotional aspects of enclosures are commonly conveyed through artistic media and representation techniques, but seldom through quantitative data driven frameworks. While the field of environmental psychology has over the years developed multiple models for the objective measurement of affective states (Russell 1980, Bradley and Lang 1994), these models have so far seldom been applied to spatial environments, thus making it difficult for designers to adopt a 'scientific approach' to the realm of spatial affect.

More importantly, the affective domain is well known to possess a great degree of 'subjectivity'. It is common knowledge that a single space can incite very different emotional responses in different occupants or user groups. Subjective experience has long been the center of phenomenological discourse, and is often attributed to factors such as cultural background and personality traits (Tweed 2000, Kuppens et al. 2013, Markovic et al. 2016) The 'positionality' of the designer thus dominates when

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engaging with design decisions pertaining to 'feelings' in spatial environments. Designers also rely heavily on their own intuitive processes when dealing with the realm of spatial affect. This subjectivity thus comes in the way of the creation of 'standards' for affective design, and counters the development of models that aim to simulate the affective dimension of space.

Nevertheless, over the past two decades, multiple studies have begun to establish frameworks for the systematic inquiry into the correlations between spatial (formal) parameters of architectural and urban enclosures, and the corresponding affective responses in occupants (Franz et al. 2003, Vartanian et al. 2013, Aspinall et al. 2013, Banaei et al. 2017, Marín-Morales et al. 2018, Sanatani 2019). Advances in simulation technologies, coupled with the rapid development and availability of virtual reality systems has opened up new methodological possibilities (Rubiyo-Tamayo et al. 2017).

Very recent advances in the application of affective computing approaches within the domain of architectural design have led to the development of models for the predictive affective evaluation of spatial enclosures (Marín-Morales et al. 2018). There have also been very initial advances by this author in the development of machine learning driven design assistance frameworks for the real-time predictive evaluation of enclosures in early stage design (Sanatani 2020). However, such research directions remain focused on the commonalities of affective experience across all subjects that constitute a dataset, rather than the subjective experiences of individual occupants or groups of occupants. There is thus immense potential for target occupant-specific affective simulation of spatial enclosures for real time predictive evaluation.

This body of research demonstrates a design assistance framework that integrates the rapid collection of target user or user-group specific affective data within an early stage design workflow, and draws upon such data for the real time affective evaluation of enclosures during design phase. The framework thus supplements the positionality and intuition of a designer with machine learning models that have been trained on user-specific datasets, thus responding to the affective nuances of the target occupant(s).

2. Affective Analysis of Spatial Enclosures

2.1 Frameworks for Affective Appraisals

While a number of models have been proposed pertaining to the structure of human emotion (Moors 2009), the Circumplex Model of Affect (Russel 1980) has been widely used within the field of environmental psychology for the objective measurement of affective states. The circumplex model comprises of the two primary dimensions of 'Valence' (Pleasant – Unpleasant) and 'Arousal' (Activated – Deactivated). According to this model, a wide range of human affective states can be represented as points within this two dimensional emotion–space. A third dimension of 'Dominance' (or Potency) is also often considered.

Based on the framework laid down by the circumplex model, Bradley and Lang (1994) developed a language independent scaling system known as the Self Assessment Manikin (SAM) for recording Valence and Arousal values in response to environmental stimuli. The SAM converted the two dimensions of the circumplex into pictorial scales for self-rating (also known as Affective Appraisals). While the SAM has been used widely in a variety of experiments across disciplines, recent methodological advances have pointed towards more appropriate frameworks for the recording of affective appraisals. Notably, the EmojiGrid (Toet et al. 2019) has been gaining popularity as an effective tool in this regard. The EmojiGrid adheres to the circumplex model, and comprises of a two-dimensional square emotion space. The emotions represented by different points along the periphery of the grid are depicted through their corresponding ‘Emojis’, with the geometric center of the grid depicting a neutral Emoji. This grid thus forms an effective and language-independent framework for the collection of affective data.

2.2 Formal attributes and emotional response

Systematic inquiries into the correlations between formal attributes of enclosures (such as shape, size, proportion, color, texture etc.) and emotional response in occupants had long been hindered by difficulties in fabricating parametrically controlled physical enclosures for experimentation. While a few early studies did embark upon such research directions, the development of virtual reality systems has sparked a renewed interest in such lines of inquiry.

Early studies examining the impact of spatial parameters of virtual enclosures on affective response revealed notable correlations between attributes such as ‘spaciousness’ and overall window area. The maxima for rated ‘beauty’ were found to correspond to length/width and width/height ratio values that were very close to the golden ratio (Franz et al. 2005). Shemesh et al. (2015) compared the emotional responses of designers and non-designers to different geometrical configurations of architectural space simulated in a visualization lab, using rating systems comprising of the scales ‘efficient’, ‘pretty’, ‘safe’, ‘pleasant’, and ‘interesting’. Banaei et al. (2017) employed EEG imaging to reveal that enclosures with higher Valence and Arousal values contained curved geometries. Pilot studies conducted by this author in Head Mounted Display (HMD) driven environments employed SAM based affective appraisals of virtual enclosures to reveal strong correlations between daylight factor and Arousal. Peak Valence values corresponded to a total-window-area/total-wall-area ratio of .03, an enclosure volume of 70 cu.m and a length:width range between 1:1 and 1:1.5. The golden ratio was not rated favorably (Sanatani 2019). Affective inquiries in the urban realm have employed mobile EEG systems and emotion recognition software to reveal reductions in Frustration, Arousal and Engagement levels when transitioning from built areas into green spaces (Aspinall et al. 2013).

The data derived through such methodological frameworks have potential to be adopted as training data for predictive affective computing. As discussed, there have been some early advances in the development of a machine learning driven design assistance framework that allow for designers to import pre-existing datasets as training data for the deployment of regression models for real time affective analysis of enclosures (Sanatani 2020). While such frameworks have potential for further development, they do not address the challenges of varying experiences across users. The need for user specific predictive affective modeling has thus become evident.

3. The Design Assistance Framework

This section outlines a design assistance framework that will allow for designers to collect such user-specific affective data for the target occupants of a function-specific spatial enclosure, and use that dataset as training data for the real-time predictive affective evaluation of the enclosure being designed.

This framework for ‘customized emotional design’ comprises of two main components – the **Data Collection Workflow** and the **Affective Analysis Workflow**. The former integrates the collection of rapid user specific affective datasets into the early stage design process, while the latter draws upon such collected datasets for real-time custom user specific affective evaluation of a design.

3.1 The Data Collection Workflow

As already discussed, the affective responses to spatial enclosures are often highly 'subjective'. Any affective analysis framework would thus have to rely upon data pertaining to the affective nuances of the target user or user groups. The Data Collection Workflow serves that specific purpose and enables the collection of user-specific affective data for predictive analysis.

For demonstration, the Data Collection Workflow was adapted for the Rhino3d + Grasshopper platform. A custom Python script within Rhino generated **100 spatial enclosures** (all bedrooms) randomized along **9 spatial parameters**, namely **length, width, ceiling height, sill height, lintel height, no of windows, window position, total window width and wall hue.** A bed, wardrobe, ceiling fan and tube-light were the only furniture/fixture items placed within each of the spaces, in fixed relative locations. These objects were placed primarily to anchor the functional specificity of the enclosure as a bedroom. In addition a dummy human figure was placed near the opposite wall to anchor a sense of scale. All such items were rendered in white, in order to retain primary focus on the spatial parameters of the enclosure. Eye height was fixed at 1500mm and camera position was fixed near one corner of the room, to allow for the subject to get a complete view of the room from the vantage point. **Figure 1** shows samples of the generated enclosure scenes. For data collection, two separate methodologies were devised for the framework, as has been detailed in the following sections.

Figure 1: Sequentially generated randomised enclosure scenes

3.1.1 Methodology 1: 2D Display with cursor control

To demonstrate the first data collection methodology, **5 subjects** (mean age 26 ± 3 years) were each asked to rate the enclosures rendered in real time using VRay for Rhino, through a **22" LED display with cursor control** for movement and 360° viewing. The ratings were in the form of affective appraisals on an EmojiGrid that appeared within the environment, near the observer's foot (Figure 2). To record their response, the subject had to click on any point on the EmojiGrid, and the Valence/Arousal ratings for the two axes would automatically be registered on a **9-point Likert scale between -4 and +4**. A dataset (.csv file) comprising of the values of the spatial parameters for each enclosure, along with their corresponding affective ratings would thus be generated for each subject.

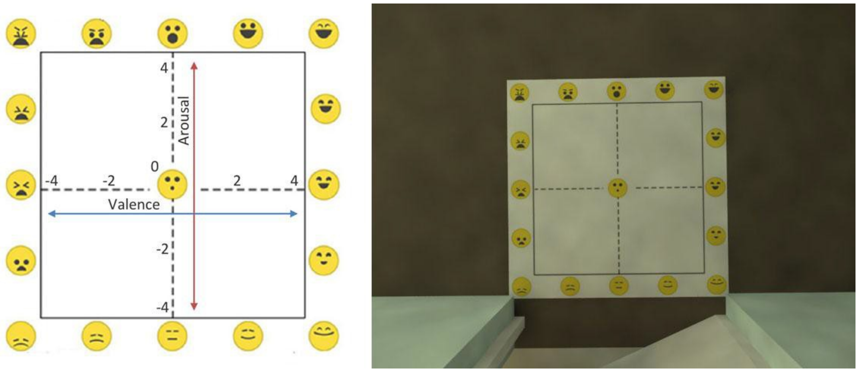

Figure 2: The EmojiGrid (Toet et al. 2019) (left) and the rating space in the display environment (right)

3.1.2 Methodology 2: 360° Immersive VR environments

In a second methodology, a custom render pipeline was scripted in Python to automatically generate **360° spherical renders** of resolution **1500 x 750** for each of the randomized enclosures using VRay for Rhino **(**Figure 3**).** A dataset comprising of the feature values for each of the enclosures was also generated as a .csv file.

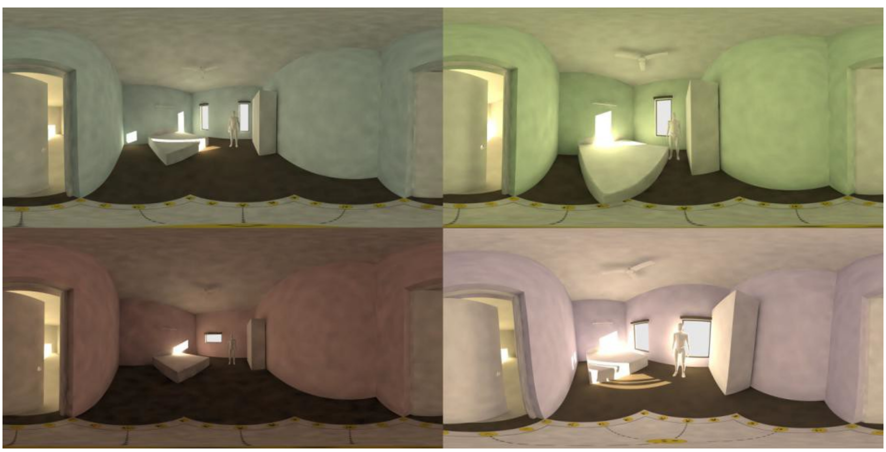

Figure 3: 360° spherical renders for immersive VR viewing

The renders were then adapted for **immersive stereoscopic VR** viewing using the Fulldrive engine and a **Head Mounted Display (HMD)** unit (Isuru Play VR)**.** The environment was also live-streamed to a laptop for real time monitoring. The subjects (the same as in methodology 1) were exposed to each scene for approximately **20-30 seconds**, and manually indicated a point on the EmojiGrid (once again appearing near the feet) for each enclosure. The ratings were converted to Valence/Arousal values and updated on the dataset. While this method provided greater realism and immersion, appropriate systems need to be adopted for the real time generation of VR scenes and the automated collection of affective response within the VR environment itself. On an average, the data collection process per subject took **20-25 minutes** to complete.

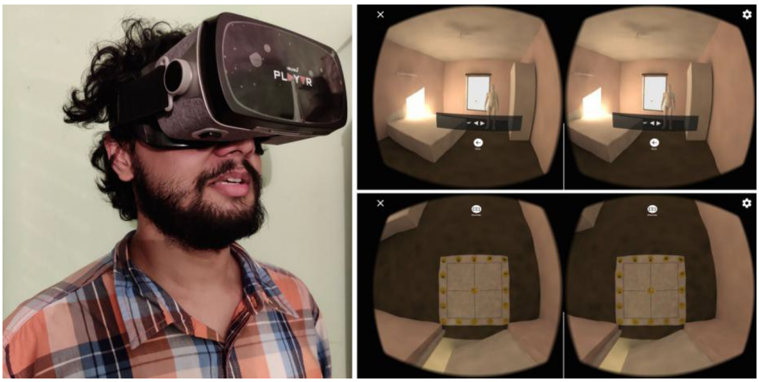

Figure 4: The HMD setup (left) and the stereoscopic VR scene for a sample enclosure (right).

The aim of the Data Collection Workflow is thus to integrate the rapid collection of user specific affective data in early stage design, for machine learning models to learn the affective preferences of the user. This serves as the foundation for real time design assistance as described in the next section. The quality of immersive visualization as well as the ease and pace of collecting data become critical in this phase. **Table 1** describes the key parameters of the datasets obtained through this workflow.

Table 1: Key dataset parameters. Val/Asl ratings are for Subject 3.

	l	b	h	sill_h	lint_h	win_no	win_pos	win_b	wall_hue	val	asl
count	100	100	100	100	100	100	100	100	100	100	100
mean	4411	4824.36	3326.01	755.37	2195.82	1.41	1926.48	1520.88	184.29	0.37	0.05
std	967.58	706.26	381.80	245.13	213.94	0.49	680.12	449.38	97.46	2.34	1.95
min	2834	3500	2710	309	1807	1	988	785	4	-4	-3
25%	3599.75	4280.75	3004.5	560.75	2006.5	1	1411.75	1125.25	104	-2	-2
50%	4385	4929	3333	725	2221	1	1734.5	1480.5	198.5	1.5	0
75%	5251.75	5452.25	3658.75	970.25	2386.5	2	2322	1908.75	255.5	2.5	2
max	5998	5987	3984	1192	2498	2	4034	2392	353	4	4

3.2 Affective Analysis Workflow

The affective analysis workflow loads custom user specific datasets for predictive real time affective analysis of designed enclosures. For demonstration, the analysis framework was scripted as a custom python component within Grasshopper3d using the GHCPython component (Abdelrahman 2017**) (**Figure 5**).** The key components of the test enclosure (such as walls, windows, floors and ceilings) had to be first defined in the Grasshopper script. The script would them compute the values for the 9 key spatial parameters. This would serve as test data for the machine learning models encoded within the custom python component to make predictions.

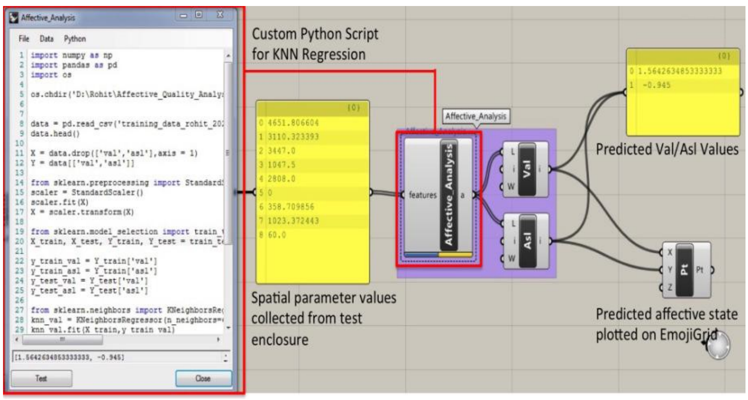

Figure 5: The custom KNN regression algorithm within the Grasshopper3d platform

3.2.1 Regression Models and Prediction Accuracy

In the current version of the framework, the python script applied a **K-Nearest Neighbor (KNN) regression algorithm** on the training data sets using the scikit-learn library (Buitinck et al. 2013), in order to make predictions of Valence and Arousal ratings. For the 5 demonstrative subjects, the model was able to predict the ratings with average root mean squared errors of **1.37** and **1.35** for valence and arousal respectively **(**on 9-point scales between -4 to +4). **Table 2** below summarizes the key error metrics for the framework. On the whole, methodology 2 allowed for greater consistency of responses within the collected dataset, and thus greater accuracy of prediction by the model.

Table 2: Key error metrics for the predictive framework (test size = 15)

	Root mean squared error					
	Val (min)	**Val (mean)**	**Val (max)**	**Asl (min)**	**Asl (mean)**	**Asl (max)**
Methodology 1	0.89	**1.34**	2.05	1.14	**1.42**	2.07
Methodology 2 (VR)	0.65	**1.39**	1.97	1.00	**1.28**	1.84

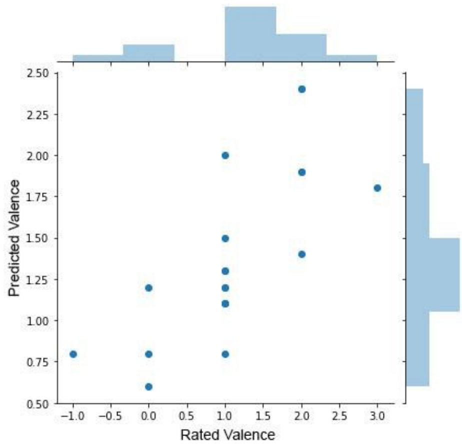

Figure 6: Predicted vs Rated values for Valence and Arousal. (Subject 2, Test size = 20)

3.2.2 The predictive evaluation interface

For design assistance, the predicted Valence and Arousal ratings as computed by the regression models would be converted into a point on the EmojiGrid, and displayed within the Rhino model space. Any changes to the formal attributes of the enclosure would result in the point being updated in the grid. This thus allowed for a real time predictive analysis of the affective impact of design decisions or design alterations. **Figure 7** below shows the affective analysis framework in action, predicting different user specific affective states for different spatial configurations for an enclosure in early stage design.

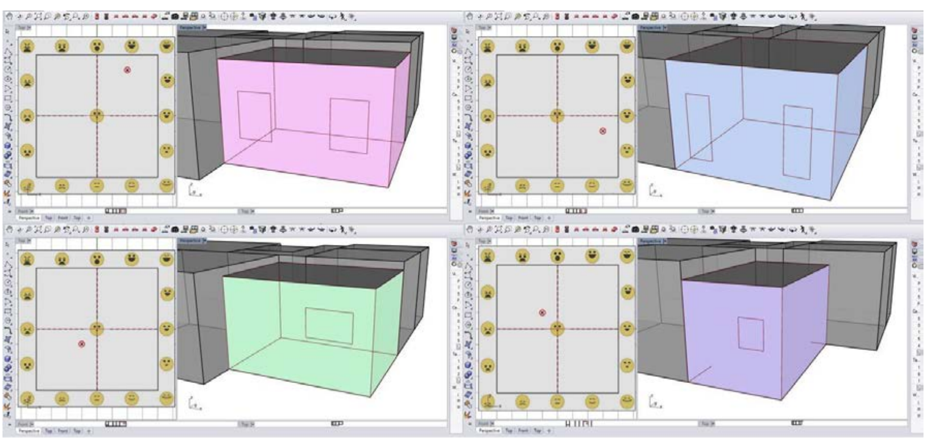

Figure 7: The Design Assistance Interface with predicted affective states reflected on the EmojiGrid.

4. Conclusion: Opportunities, Challenges and Future Directions

The design assistance framework described in this paper attempts to integrate rapid affective data collection and real-time analysis into the early stage spatial design process. Most importantly, it is a step towards integrating user-specific and 'subjective' patterns of affective response into a computational framework, thus opening up possibilities of the emotional customization of spaces.

As discussed right at the outset, this framework situates itself within a very nascent research direction, and thus has much scope for further development and refinement. The data collection process in VR was described as tiring by multiple subjects, largely due the fact that the HMDs had to be worn continuously for the test duration. This would certainly have had an impact on the affective states of the subjects towards the end. A robust data collection methodology involving real time generation of randomized enclosures for immersive VR viewing and rapid appraisal thus needs to be synthesized. This will considerably increase the accuracy of the affective data collected, thus enhancing the reliability of the predictive analysis. Architects have a limited time of engagement with clients, and an immersive yet quick framework becomes the key to smooth collection of affective data. For the affective analysis component as well, more appropriate machine learning models need to be deployed for greater accuracy of predictions. The average root-mean squared error of ~1.36 of the predictions needs to be improved if the framework is to mature into a viable supplement to the designer's intuitive processes.

There is great potential for the entire framework to be developed as plugins for existing early stage design platforms, which will allow architects to rapidly collect affective data directly from clients, or from representatives of target user groups, and use these custom datasets for real time affective analysis of design outcomes. There has been rapid development over the years in virtual/mixed reality collaborative design platforms (Penn et al. 2004, Belcher et al. 2008, Schubert et al. 2015, Dorta et al. 2016), and the adoption of such platforms for the collection and analysis of affective data can open up new possibilities. Moreover, such predictive models can also plug into existing algorithmic and evolutionary floor plan generation frameworks, as a tool for the optimization of affective parameters. There is also scope for such a predictive framework to provide an affective dimension to the future of dynamic or parametrically alterable physical structures, where such enclosures may be able to change their form based on a desired 'mood' of the occupant. It is hoped that such directions towards engaging with user-specific spatial affect opens up new dimensions to the role of the architect in the near future.

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