

A MACHINE-LEARNING DRIVEN DESIGN ASSISTANCE FRAMEWORK FOR THE AFFECTIVE ANALYSIS OF SPATIAL ENCLOSURES

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Abstract. There is a growing research direction that adopts an empirical approach to affective response in space, and aims at generating bodies of quantitative data regarding the correlations between spatial features and emotional states. This paper demonstrates a machine-learning driven computational framework that draws upon training data sets to predict the ‘affective impact’ of designed enclosures. For demonstration, it has been scripted as a Rhinoceros + Grasshopper based design tool that uses existing training data collected by the author. The data comprises of the spatial parameters of Enclosure Volume (V), Length/Width ratio (P) and Window Area/Total Internal Surface Area ratio (D) - and the corresponding emotional parameters of Valence and Arousal. The test values of these parameters are computed by defining the components of the test enclosure (walls, windows, floors and ceilings) in the script. Nonlinear regression components are run on the training datasets and the test input data is used to compute and display the real time predicted affective state on the circumplex model of affect.

Keywords. Affective Analysis; Affective Computing; Design Assistance; Machine Learning; Spatial Enclosures.

1. Introduction

The affective or emotional qualities of spatial enclosures have often been regarded as ‘intangible’ aspects of space beyond the scope of empirical inquiry. While it is well known that different ‘kinds’ of spaces affect us in different ways and elicit different emotional responses, architects have traditionally relied on intuition when engaging with design decisions pertaining to the affective domain. While there are well-established standards, models and design assistance tools for the design of other aspects of enclosures such as energy optimization, acoustics etc., there are few such supporting frameworks for the affective realm. Till recent years, a lack of empirical lines of inquiry into the affective qualities of spatial enclosures made it difficult for designers and architects to adopt a ‘scientific approach’ to the realm of emotional response in space. However, recent lines of inquiry have established frameworks for the systematic study of the correlations between specific attributes of the form of virtual enclosures, and corresponding emotional

response in occupants (Franz et al. 2003, Vartanian et al. 2013, Marín-Morales et al. 2018, Sanatani 2019). Challenges of generating parametrically controllable physical enclosures for experimentation have been overcome with advances in simulation technologies, and virtual reality systems. The rapid development and commercial availability of head mounted display driven VR apparatus have opened up new methodological possibilities for such research directions (Mazuryk and Gervautz 2010). Despite being an emerging line of inquiry, there is a growing body of data pertaining to the emotional impact of specific formal parameters or ‘features’ of spaces (such as geometric configuration, size, color, texture etc). Such studies directed specifically towards the effect of specific spatial parameters on emotional response has the potential to open up very valuable lines of enquiry into the correlations between the physical and the emotional realms within space. Most importantly, the body of empirical data generated can provide architects with strong rational grounding to design decisions pertaining to spatial experience.

The field of affective computing or ‘artificial emotional intelligence’ has seen rapid development since its inception two decades ago. Today, there are computational models and frameworks in place capable of recognizing emotional states based on facial expressions (Robinson and el Kaliouby 2009). Inquiries have been made into the correlations between features of photographs, and the corresponding emotional response and aesthetic judgment in observers (Datta et al. 2006). However it has only been in the past couple of years that affective computing has begun to be applied to the domain of spatial enclosures and architectural research (Marín-Morales et al. 2018). Such research directions have a strong potential to be taken forward in order to yield computational models for emotional response in space. The body of labeled empirical data gathered through such inquiries has immense potential to be used as training data for machine learning algorithms designed to ‘learn’ underlying patterns between spatial ‘features’ of enclosures and affective states in occupants. This can be taken forward to develop design assistance tools, which can employ machine-learning models to predict the emotional impacts of designed enclosures.

This paper demonstrates a computational framework for generating a design assistance model that predicts the emotional impact of a designed enclosure in real time based on specific spatial features, by applying non-linear regression algorithms to existing training data sets collected from prior experiments.

2. Quantifying affective response in space

Any line of empirical inquiry focusing on emotional response in space must first adopt or synthesize a framework for the collection of objective and quantifiable data pertaining to one’s emotional state. While a number of models have been proposed as structures of human emotion, there have been two broad approaches towards structuring the affective realm.

Basic Emotion Theories/Discrete Theories maintain that there are sets of very basic and discrete human emotions, such as Joy, Disgust, Surprise, Fear, Anger and Distress (Ekman 1984), which cannot be broken down into simpler parts. These emotions lie within separate domains and are discrete in nature.

More recent schools of thought however opine that all emotions can rather be mapped on dimensional scales such as the Circumplex model (Russell 2003). The circumplex model consists of a three dimensional emotion-space with Valence (Pleasure-Displeasure) on the x axis and Arousal (Activation-Deactivation) on the y-axis. The z-axis of Dominance is also often used. According to this Dimensional Theory, a wide range of possible human emotions can be defined with respect to these basic dimensions. (Figure 1)

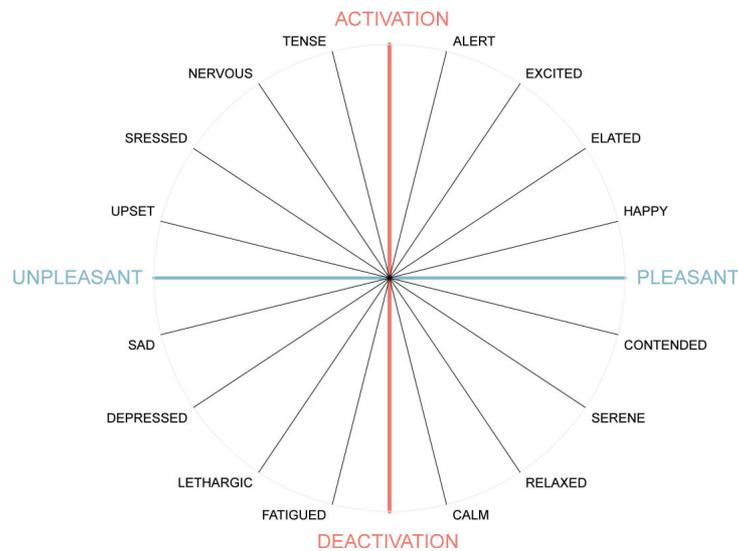


Figure 1. The Circumplex Model of Affect (Russell 2003).

One approach towards the objective recording of emotional response focuses on recording the physiological and biological indicators that accompany emotional response, such as facial expression, Electro Dermal Activity (EDA), Skin temperature (SKT), and Electrocardiography (ECG) (Kim et al. 2003). A large amount of emotional data collected for affective computing is in the form of such indicators. However, a number of methodological difficulties pertaining to the accuracy and relevance of such biological parameters as indicators of spatial affect have been highlighted in past studies (Hermund et al. 2019). Notably the sensitivity of the recording equipment to extraneous electrical signals, especially from the wearable VR systems is a factor that needs to be dealt with.

A second approach relies on one's own verbal assessment of his or her emotional response to any given stimulus (known as an 'affective appraisal'). Affective appraisals thus assume the accuracy and reliability of one's own conscious affective assessment. Bradley and Lang developed a language independent scaling method for recording appraisals known as the Self Assessment Manikin, which is now regularly employed in experiments for measuring a range of emotional stimuli. In this method, the two dimensions of human emotion (Valence and Arousal) are represented as pictorial scales. (Bradley and Lang 1994)

In one of the early studies enquiring empirically into the affective qualities of spatial enclosures in virtual reality, Franz, von der Heyde and Bulthoff studied the architectural parameters such as Total Window Area, Wall Openness Ratio,

Size of Single Window, Room Area, Room Length/Width etc. and their effects on spatial experience (Franz et al. 2003). Subjects were asked to rate parametrically altered variants of a designed virtual enclosure on a semantic differential scale with bipolar adjectives such as unpleasant-pleasant, boring-interesting, ugly-beautiful, arousing-calm etc. Notably, they found 'spaciousness' to be correlated more strongly to overall window area as compared to actual room area. The maxima for rated beauty corresponded to length/width and width/height ratio values which were very close to the golden ratio (Franz et al. 2003).

A related experiment by Shemesh, Bar and Grobman was directed towards testing the emotional responses of two sets of subjects - designers and non-designers - to different geometrical configurations of architectural space (smooth, curvy, symmetrical, asymmetrical etc) simulated in a visualization lab comprising of high-definition projection and motion sensors (Shemesh et al. 2015). A rating system comprising of the scales efficient, pretty, safe, pleasant, and interesting was used. The results indicated that both the groups appeared to prefer asymmetric spaces to symmetric ones. The non-expert group however found familiar spaces to be much more pleasant as compared to unfamiliar configurations. However the curved configuration (despite being unfamiliar) corresponded to a high degree of rated 'prettiness' and 'interestingness'. The round space however was more interesting and pretty to the expert group (Shemesh et al. 2015).

Outside the domain of spatial enclosures, McDuff et al synthesized a machine learning driven framework for predicting the affective states of individuals at their workstations (McDuff et al. 2012). They relied on labeled training data collected from five participants over two days. The independent variables or features logged included facial expression features decoded from a webcam stream, voice features decoded from microphone data, electro dermal activity (EDA), posture and file activity. The output data included Valence, Arousal and Engagement ratings normalized to produce discrete labeled classes corresponding to emotional states on the circumplex. A nearest neighbor classifier model was used to make predictions based on test data and the results were logged and displayed to the users.

Morales et al. applied statistical analysis and machine learning models to data sets correlating spatial parameters such as Geometry (Curvature, Complexity, Order), Color (Tone, Saturation, Value) and Illumination (Color temperature, Intensity, Position), and the corresponding biological indicators of heart rate variability and electro encephalic signals, collected through experiments conducted using HMD driven VR environments. Affective appraisals of the subjects were also recorded on dimensional emotion models using the self-assessment manikin (Marín-Morales et al. 2018). A support vector machine classifier algorithm was employed to predict the valence and arousal states of subjects with more than 70% accuracy. The methodology synthesized for these experiments show great potential to be adopted for focused research within the domain of spatial affect, and data collected through such experiments can be used as training data for machine learning algorithms to 'learn' underlying relationships between spatial features and emotional response.

3. The demonstrative training dataset

To demonstrate the computational framework presented in this paper, a pre-existing dataset has been adopted, which was collected through an earlier phase of empirical experimentation conducted by the author.

The experiments focused on deriving correlations between three spatial parameters or 'features', namely: (i) Area of glazing/Total internal surface area (**D**), which is the primary variable for daylight factor, (ii) Total volume of enclosure (**V**) (iii) Length/Width ratio of the enclosure (**P**) (Sanatani 2019).

Through three separate sets of experiments, 18 parametrically altered variants of an empty spatial enclosure corresponding to varying values of each of the three spatial parameters were presented to 50 subjects through a head mounted display (HMD) driven virtual reality system. Each of these scenes were spherical renders of field of view (FOV) 360° and resolution 4000x2000 pixels generated using Rhinoceros and Grasshopper3D, rendered using VRay for SketchUp and adapted for VR viewing through FullDrive VR (Sanatani 2019).

Subjects were asked to rate each space on the Self Assessment Manikin, the results of which were then converted into numerical Valence and Arousal scores on a -4 to +4 scale. Each set of experiments thus gave us two sets of 300 data points describing the variation in each of the dependent variables (arousal and valence) due to controlled variation of the independent variable (the spatial parameter being studied). The training dataset thus comprises of total of 900 data points each for Valence and Arousal.

A cursory analysis of the data revealed that daylight factor correlated very strongly with Arousal. Peak Valence values corresponded to a wall/window 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).

The dataset collected from these experiments has been adopted to demonstrate the computational framework and serve as training data for the machine learning algorithms to learn the predominant patterns.

4. The computational framework

4.1. THE PLATFORM

The framework described in this paper has been developed on a Rhinoceros + Grasshopper platform, with the additional use of the nonlinear regression component provided for Grasshopper by the machine learning tools within the Lunchbox plugin. While this platform has been adopted for demonstration, it may be coded onto more appropriate platforms in the future. Existing python libraries (such as scikit-learn) can be employed for greater flexibility and control over the model. The framework also has potential to be developed as a separate plugin to Rhinoceros, or even as a standalone design assistance tool.

4.2. THE FRAMEWORK

The computational design assistance framework presented in this paper comprises broadly of three parts or units and has been conceptually summarized in Figure 2.

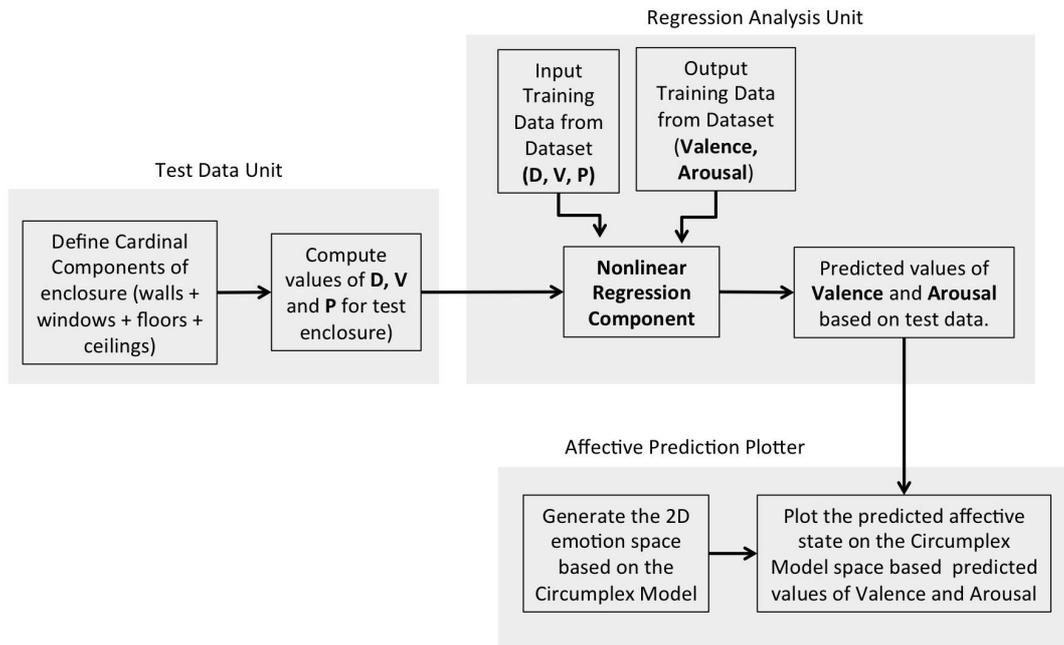


Figure 2. Conceptual representation of the design assistance framework.

The first part or the **test data generation unit** defines the cardinal components of the modeled test enclosure (such as walls, floor, roof, windows) into the Grasshopper script and subsequently computes the real-time values of the three spatial parameters (namely D , V and P). Figure 3 shows a conceptual representation of the grasshopper script corresponding to this unit.

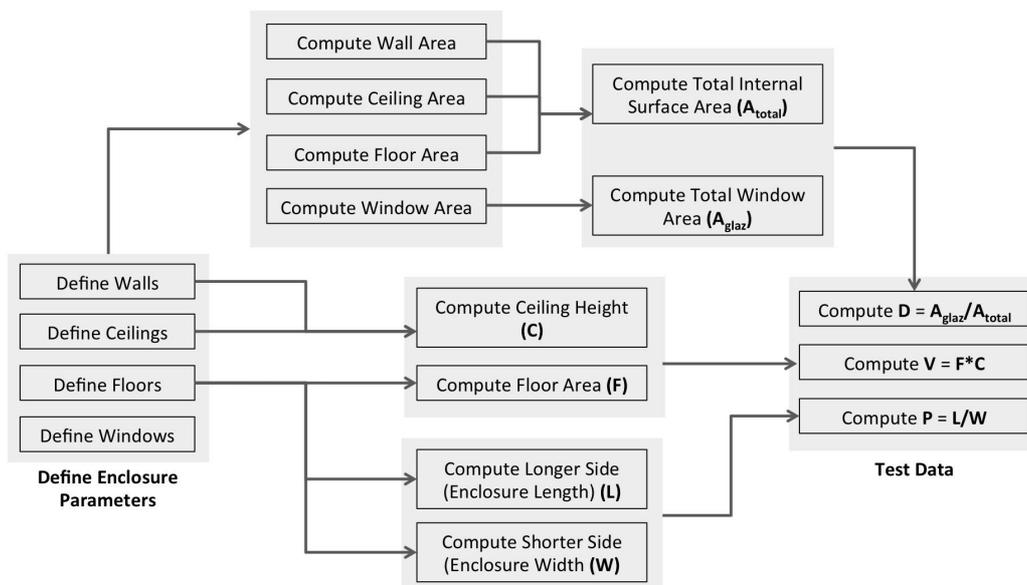


Figure 3. Conceptual script for the test data generation unit.

The second unit of the framework or the **regression analysis unit** runs the

main Multivariate Nonlinear Regression algorithm. The Nonlinear Regression component provided by Lunchbox for Grasshopper accepts the training data from the adopted dataset. The input training data is thus the 900 values of A, V and P respectively. The output training data for each set are the 900 corresponding values each of valence and arousal. There are thus two nonlinear regression components running i.e one for valence and one for arousal. These components output the real time predicted values of Valence and Arousal for the test enclosure.

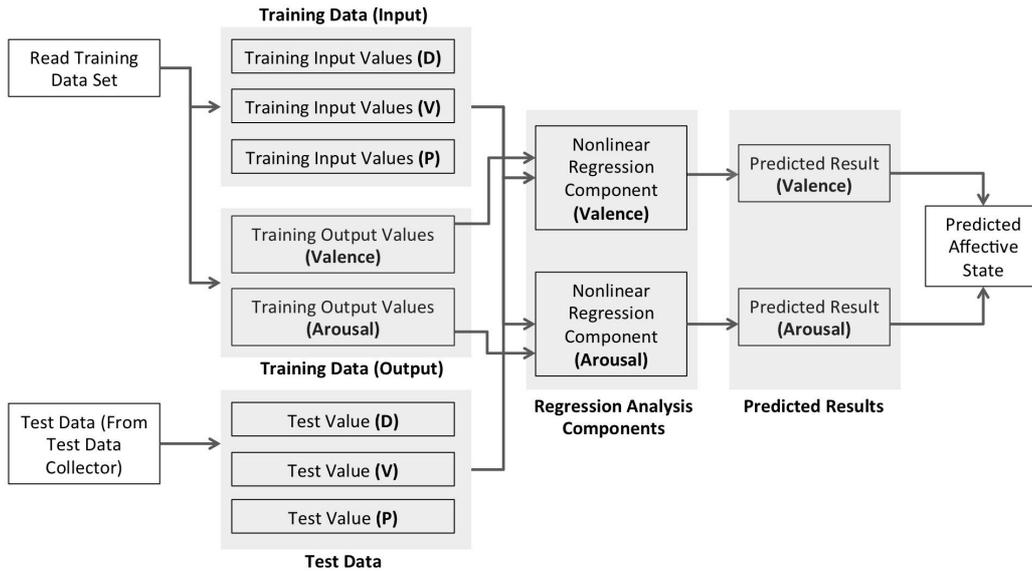


Figure 4. Conceptual script for the regression analysis unit.

The third unit of the computational framework or the **affective prediction plotter** generates the representative 2d affective space based on the circumplex model of affect in the Rhino modelspace. It then inputs the predicted values of valence and arousal from the previous unit and plots the predicted emotional state on the circumplex, thus allowing the designer to view real time shifts in affective states based on changes in spatial features made to the test enclosure.

Figure 5 and Figure 6 demonstrates the working of the tool. For a designed enclosure of $V = 70.38$ cum, $P = 1.0$ and $D = .03$, the nonlinear regression component predicts an affective state of Valence = +2.36 and Arousal = +1.95 and displays it as a point on the circumplex emotion space. When the spatial features of the enclosure are modified, changing the values of V, P and D to 428.43 cum, 2.15 and .0083 respectively, the shift in predicted affective state to Valence = -1.09 and Arousal = -.02 is reflected on the circumplex. This real time interface thus allows the designer to constantly monitor the affective implications of his design decisions pertaining to spatial features.

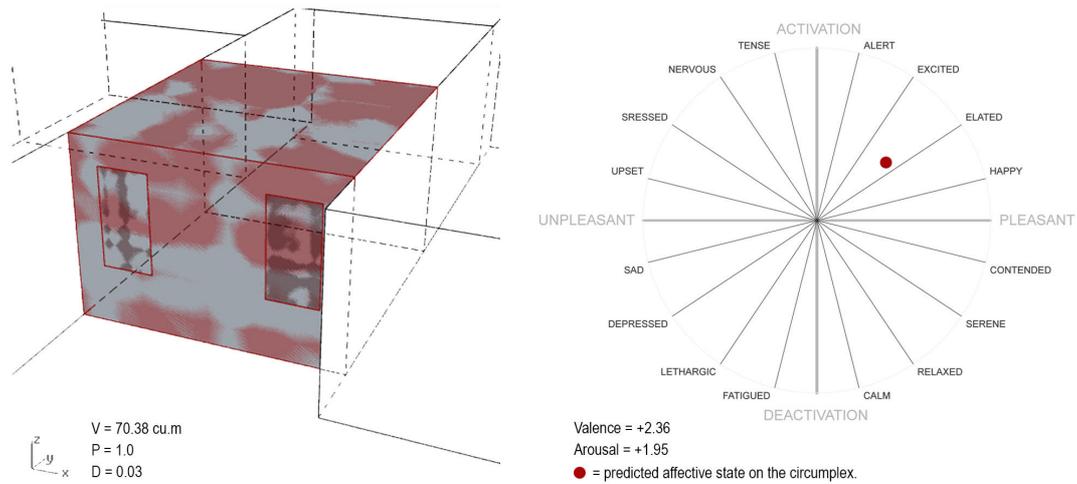


Figure 5. Predicted affective state for $V = 70.38$ cum, $P = 1.0$ and $D = .03$.

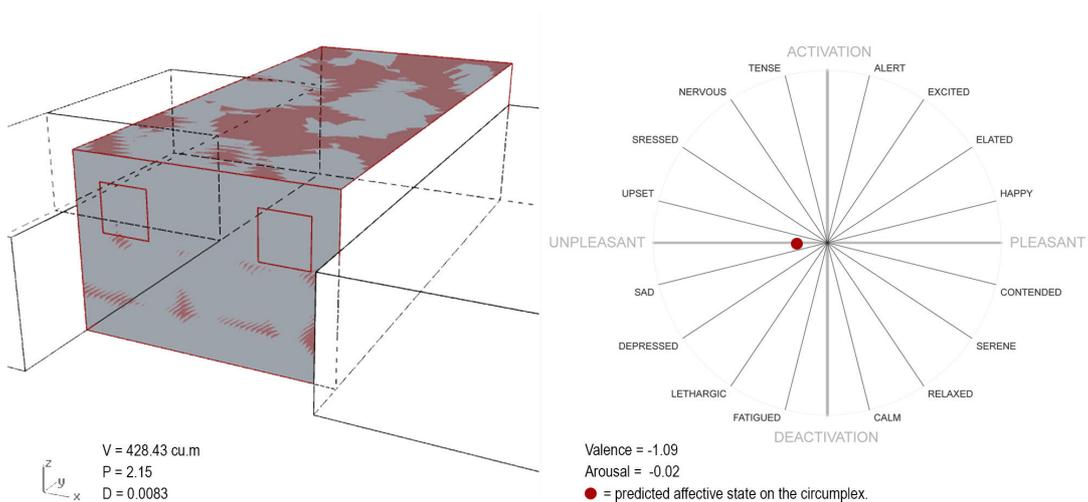


Figure 6. Shift in predicted affective state for $V = 428.43$ cum, $P = 2.15$ and $D = .0083$.

It may be mentioned here that the adopted demonstrative training data set has its limitations with respect to multivariate regression analysis. As discussed earlier, the data set was collected through 3 sets of controlled experiments corresponding to the three spatial parameters, with only a single parameter being varied in each set. For the multivariate regression model to have greater accuracy, the training data set should have data points corresponding to simultaneous variations in all the independent variables. For the current data set, three sets of bivariate regression analysis components will produce more accurate results. However, for demonstration of the framework, a multivariate model has been adopted, which can be applied to more appropriate datasets in the future.

5. Conclusion and future directions

The aim of this framework is to draw upon empirically derived training data in order to allow machine learning algorithms to learn underlying patterns in the ways in which specific formal attributes or ‘features’ of spatial enclosures impact affective states, thus allowing for real time predictive analysis of the affective qualities of enclosures during the design phase. As discussed earlier, while there are numerous design assistance and simulation tools for aspects of design such as energy performance or acoustic behavior, architects still rely primarily on their own intuitions when designing for the affective realm. While the field of affective computing has made rapid progress in applying quantitative and computational processes to make sense of the affective domain, this field has only very recently begun to foray into the world of architectural design. The framework presented in this paper aims to serve as a small yet firm step towards applying the processes of affective computing directly in the design process.

The demonstrative training data set drawn upon in this paper may be replaced by much larger and more accurate data sets, which will result in more accurate predictions. Moreover, such a framework has immense potential to be applied to occupant-specific datasets for algorithms to learn the affective patterns of the target occupant(s) in space, thus working towards the creation of tailor-made spaces that respond to the affective nuances of the individual(s). There are an incalculable number of spatial features that affect our emotional response in spaces, and this framework need to be expanded to include many more parameters such as color temperature, texture, geometry, opening configurations etc. which play vital roles in determining how the space makes us ‘feel’. In the age of big data, we have a plethora of new sources through which data pertaining to one’s emotional state may be obtained. It is hoped that data obtained through larger focused studies conducted in the future, or even through crowd sourced data collection systems, can plug into this framework and lead to the development of a design assistance tool that can aid architects in designing for the affective domain.

On a concluding note, one may reflect upon what such research directions will mean with respect to the role of the architect in the future. The advent of computer aided drafting tools has greatly reduced the time required in preparing architectural drawings and revisions. The advent of Building Information Modeling (BIM) systems has dramatically reduced the man-hours spent in coordination between consultants and compiling building related data. Rapid advances are currently being made in the field of automated floor plan generations based on preset constraints and design briefs (Nisztuk and Myszkowski 2019). It has often been argued that the one domain within which automation cannot replace the human mind is the domain of subjective phenomenological experience. Computers, it has been said, cannot ‘feel’ or design for ‘feelings’. The domain of affective computing however has been steadily proving otherwise. As discussed, algorithms are learning to predict what images and graphics will make people feel, and are also beginning to generate graphics that are intended to make people ‘feel’ certain ways. Where then, lies the role of the artist? Can we envision a future where algorithms are not only equipped to generate floor plans, but also design spaces that will make users ‘feel’? Where then, lies the role of the architect?

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