Human Nonverbal Behaviour Understanding *in the Wild* for New Media Art

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Abstract. Over the course of the London 2012 Olympics a large public installation took place in Central London. Its premise was to enable members of the public to express themselves by controlling the lights around the rim of the London Eye. The installation's design and development was undertaken as a collaborative project between an interactive arts studio and researchers in the field of affective and behavioural computing. Over 800 people participated, taking control of the lights using their heart rates and hand gestures. This paper approaches nonverbal and affective behaviour understanding for new media art as a case study, and reports the design of this installation and the subsequent analysis of over *one million frames* of physiological and motion capture data. In doing so it sheds light on how the intersection of affective and behavioural computing and new media art could be beneficial to both researchers and artists.

Keywords: New media art, affective behaviour understanding in the wild, gestural interaction, mood, nonverbal behaviour.

1 Introduction

New Media Art is defined as art that utilises new media, such as digital electronics, computer animation, interactive interfaces or networked communication [1]. In many cases, these media comprise the very same tools that affective and behavioural computing researchers are adopting for the computerised recognition and expression of human nonverbal behaviour and affect. Despite this plurality, there is currently very little exploration or utilisation of affective and behavioural computing techniques in artistic practices. This is surprising, given the important roles that nonverbal behaviour and affect play in creative expression and experience [2]. As affective and behavioural computing starts to migrate from the laboratory and into the wider world, the question of whether artists will welcome affective and behavioural computing based technologies as a positive addition to their new media palettes is likely to come to the fore.

During the summer of 2012 we undertook a collaborative project with Cinimod Studio - an interactive arts studio based in London. The project involved both artists and researchers in affective and behavioural computing and led to the design and analysis of a high profile interactive installation called the Mood Conductor. Our work was conducted *in the wild* (non-laboratory settings) and consequently this paper approaches nonverbal behaviour analysis as a case study, when subjective evaluation of the user experience cannot be obtained. We report the design of the installation and the subsequent *unsupervised* analysis of over *one million frames* of physiological and motion capture data. By presenting and discussing the processes, challenges and results of this study, we hope to provide valuable insights into the nature of the intersection of affective and behavioural computing and new media art practices.

2 Background

Physiological measurement and gesture recognition are two techniques that have been adopted by technologists, artists and researchers in order to enrich the ways we interact with computers, artworks and creative installations. However, there has been little cross-pollination of ideas between the commercial and academic worlds. While researchers attempt to identify affective states from measurable components of nonverbal behaviour and physiology, artists and technologists are creating entities that enable new forms of expression. The project discussed in this paper combined both physiological and gestural measurements in an attempt to bring an affective and behavioural dimension to a large public installation.

2.1 Heart Rate Measures, Affect and Art

In the field of psychophysiology many studies have been carried out which attempt to quantify the physiological aspects of different emotions [3–5]. The most commonly measured variables are galvanic skin response (sweating), breathing rate, muscle contraction, pupil dilation, and cardiac output (e.g. heart rate, blood pressure, heart rate variability) [6]. Heart related measurements are particularly attractive to affective and behavioural computing researchers due to the fact that changes in cardiac output occur very quickly in response to external stimuli. In a study of emotional reactions to video game events Ravaja et al [7] found that phasic heart rate changes occurred in response to specific game events. Rewarding and positive game events were accompanied by an increase in heart rate, whilst the authors suggested that decreases in heart rate could be associated with a rise in attentional engagement. In relation to sadness, a study of emotion during musical performance observed a decrease in average heart rate when musicians performed under the condition of induced sadness relative to performances in which they merely expressed sadness [8]. Heart rate changes in response to negative emotional stimuli have also been found to be more prolonged when compared to equivalent exposure to positive stimuli [9]. The main challenge in using heart rate as a reliable indicator of affect is that it is necessary to control for the numerous variables that can affect a person's heart rate. These include health factors, physical exertion and the influence of drugs such as caffeine. In laboratory based experiments it is possible to account for these extra variables using controlled settings, subject profiles and questionnaires. However, if we are to use heart rate measures in media and arts applications *in the wild* there is a much greater challenge in extracting meaningful data from heart rate measures alone.

2.2 Hand Gestures, Affect and Art

One of the first gestural interfaces was the Theremin [10], a musical instrument which creates sound oscillations with varying frequency and amplitude according to the position of the player's hands relative to two antennas. The Theremin serves as a good example of the design considerations that should be made when using gestural input as a control interface. Sturman and Zeltzer [11] formalise these considerations and organise them as sequential stages in the design process. The initial stage involves assessing the *appropriateness* of whole hand input as a method of interaction by considering its distinguishing features - naturalness, adaptability, coordination and real-time control. The second stage concerns *taxonomy* - distinguishing which styles of whole-hand input will fit the application. Sturman and Zeltzer organise the expressivity of the hand into two categories - *continuous features*, which concern quantifiable measurements of the physics of the hand (e.g. force applied, and degrees of rotation); and *discrete features* that refer to symbolic 'input tokens' such as postures (e.g. thumbs-up) or gestures (e.g. waving). The third and final stage involves the matching of 'task primitives' to particular hand actions. In the case of the Theremin the primitives are pitch and amplitude adjustment, and the actions are the continuous movement of the hands in three dimensions.

In more recent years the release of open source drivers for the Microsoft Kinect has provided an accessible way for artists and interaction designers to work with motion capture based gesture recognition. When looking at examples of the use of the Kinect in these contexts (see [12] and [13] for specific works), a common feature is that less defined input to output mappings are used, an approach which puts more creative freedom in the hands of the person using the interface. The LEAP motion sensor, released in July 2013, purports to be able to measure finger movement to a resolution of 0.01 millimetres. Technologies like this will undoubtedly contribute towards on-going advances in the measurement of fine-grained gestures.

The Component Process Model (CPM) [14] breaks emotion down into five components - cognitive, neurophysiological, motivational, motor expression and subjective feeling - each with associated functions and 'organismic subsystems' [15]. The study of affective gestures relates to the motor expression component of this model - the movement of joints, muscles and limbs. In a study of the perception of affect from arm movement, Pollick et al. [16] used point-light displays to represent knocking and drinking movements, each performed with ten different affects (afraid, angry, excited, happy, neutral, relaxed, sad, strong, tired, and weak). They found that the arousal dimension [17] of each affective state had a strong correlation to kinematic features of the movement such as velocity, acceleration and jerk. Similar experiments have since supported this link between emotional arousal and motion [18, 19].

3 Design and Development

Cinimod Studio[1] were commissioned to create an installation which would enable members of the public to represent their *mood* by taking control of the lights on the London Eye. Participants would be invited free-of-charge to step onto a podium for roughly one minute, during which they would be able to use the motion of their hands to control the 320 lights which line the rim of the Eye.

3.1 Design

Simplicity was one of the main concepts that guided the design process. Given the potentially short amount of time that each participant would have to interact with the installation, the following were identified as prerequisites: (i) ensuring that the participants would not spend a majority of the time trying to understand how their movements affected the lights, and (ii) making the sense of *control* clear and powerful by focusing on direct mappings of hand and arm movements to lighting changes, as opposed to recognising and responding to specific symbolic gestures.

The Kinect SDK was used to track the position of each of the participants' hands and the centre of their body (torso). The angles between each hand and the torso (along the coronal plane) were then directly mapped to the angular positions of two segments of lighting content on the perimeter of the Eye (see Fig. 1). In order to create a robust motion tracking system the Kinect data was passed through three stages of processing: (i) detecting the current user and extracting joint coordinates (shoulder, elbow, hand, etc.), (ii) filtering to discard false participants based upon coordinate positions and quantity of motion, and (iii) smoothing the motion data and calculating hand-torso angles to be used by the lighting content generator.

Three *distinct lighting content styles* were designed in order to give some aesthetic variation to the artwork. We also wanted the variation in these styles to be somewhat representative of different mood states. The three styles were named Wave, Fire and Spectrum (see Fig. 2). *Wave* had a sense of calmness (a low arousal, high valence mood), simulating the fluidic motion caused by waving your hands in a pool of water. *Fire* gave the impression of juggling with flaming torches, which we associated with high arousal moods. *Spectrum* was the most colourful of the three and had a sparkling appearance that gave it a sense of representing high valence (positive) moods. Since the Eye was rotating during the installation, a gyroscope (positioned on the rim of the Eye) was used to sense the angle of rotation and correct the orientation of the lighting content so that it did not appear to move with the Eye.

[1] http://cinimodstudio.com/

The inclusion of a pulse rate sensor was intended to provide an additional, symbolic means of representing the participants' moods through the lights on the Eye. We built a custom heart rate monitor, which used a photo-plethysmographic ear-clip sensor coupled with an analog switch. The signal from this was then transmitted wirelessly (using XBee modules). The resulting device was small enough to be worn around the neck, and could be quickly transferred between participants. An additional lighting content feature was developed, allowing the participants to view their heart beats as a pulsing red strip of lights at the top of the Eye. The feature was triggered when a participant held their hands still for longer than three seconds. The software for processing the inputs from the Kinect and pulse monitor was developed using VVVV, a visual programming environment which has inbuilt support for Kinect, as well as DMX protocol lighting output. An overview of the full system is given in Fig. 1.

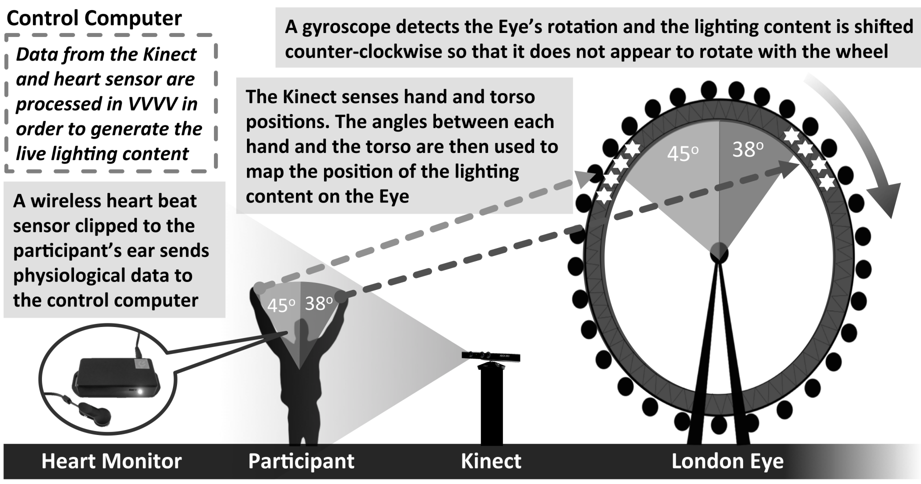


Fig. 1. System diagram detailing the basic setup and functioning of the installation

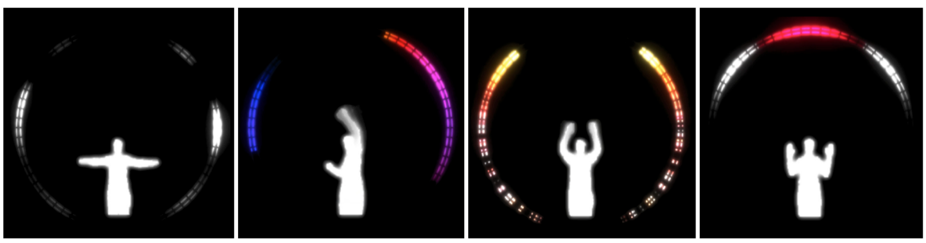


Fig. 2. Content styles: (from left) Wave, Spectrum, Fire, Wave with heart pulse feature

3.2 Mood Profiling

We decided to assign a fixed content style to each participant. It would be confusing if the content style changed, especially given the short time people had to explore the installation. As previously discussed, heart rate and kinematic features of gesture have been shown to be linked to the arousal dimension of affect. By analysing each participant's initial motion and heart rate data, we created a snapshot profile of their mood state which was then used to select the content style.

The profiling was performed at the beginning of each participant's turn (first 5 sec). Content choice was implemented by assigning a score to each of the three content styles based upon weighted contributions of six features: the *average heart rate* and five kinematic variables - *fluidity, angular motion, range of depth, average height and unique movement.* The contribution of these factors to each content score is shown in Table 1. Heart rate thresholds were chosen based on the average median, maximum and minimum heart rates for a healthy individual.

Table 1. Content scoring criteria

Content Style	Positively Contributing Factors	
	Heart Rate (bpm)	**Kinematic**
Wave	<80	Fluidity, low average height
Spectrum	80 - 100	Unique movement, range of depth
Fire	>100	Angular motion, high average height

For each participant the highest scoring content style was selected for the duration of their turn on the installation. For example, if the participant waved their hands high and had a heart rate above 100 bpm then the system would select the Fire content for them. The five kinematic features of hand movement are described in more detail below.

1. **Fluidity**(flu): A measure of the uniformity of motion [18], calculated based upon the variance in the first n velocity values for each hand,

$$flu = \frac{1}{n}\sum_{i=1}^{n}(v(i) - \mu)^2 \tag{1}$$

where μ is the average velocity over first n samples and $v(i)$ is the *velocity* at sample i:

$$v(i) = \frac{\sqrt{(x_i - x_{i+1}))^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2)}}{t_{i+1} - t_i} \tag{2}$$

$(x_i, y_i z_i)$ are the $3D$ coordinates of the hand at sample i, and t_i is the time at sample i.

2. **Angular motion (m_α)**: A measure of amount of rotational movement of the arms, calculated by finding the range in the first n angle values.

$$m_\alpha = \max_{i=1}^{n}(\alpha(i)) - \min_{i=1}^{n}(\alpha(i)) \tag{3}$$

where $\alpha(i)$ is the angle value for the ith sample:

$$\alpha = \arctan 2(y_h - y_t, x_h - x_t) \tag{4}$$

(x_h, y_h) is the $2D$ position coordinates of left or right hand, and (x_t, y_t) is the $2D$ position coordinates of the torso.
3. **Range of depth(rd)**: Calculated as the maximum range in the first n depth range values along the Z axis (depth) for each hand.

$$rd = \max_{i=1}^{n}(z(i)) - \min_{i=1}^{n}(z(i)) \tag{5}$$

4. **Average height(h)**: Calculated as the average of first n height values along the Y axis (vertical) for each hand.

$$h = \frac{1}{n}\sum_{i=1}^{n} y(i) \tag{6}$$

5. **Unique movement**: A measure of the uniqueness of the hand movement during a given sampling period. This was calculated using a function in $VVVV$ which outputs the number of unique coordinates in an array containing all of the hand coordinates over n samples. For example, if someone kept their hand still for the duration of the sampling period then there would only be one unique coordinate value (uniqueness = 1), whereas if they waved their hand between multiple positions the uniqueness value would be greater, reflecting the number of positions their hand covered.

4 Data Analysis and Results

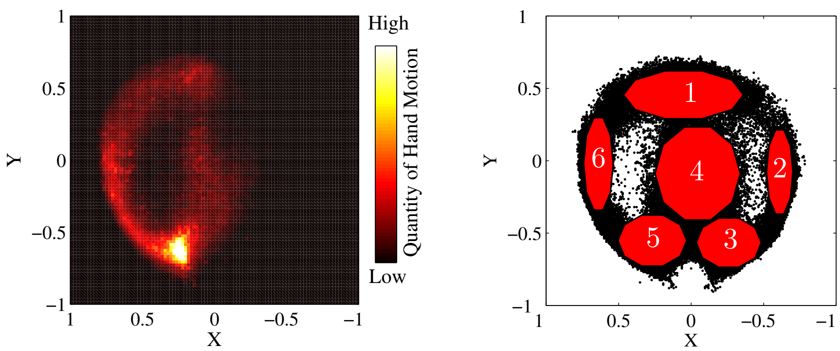
Due to the restrictions of collecting data *in the wild* we were aware that our ability to draw significant conclusions from our data analysis would be somewhat restricted. For example, we were unable to collect video data or subjective feedback from participants. Consequently we approached our data analysis with an intention to broadly investigate the outcomes of applying affective and behavioural computing inspired techniques in a real-world interactive media and arts context. More specifically, the goal was (i) to explore the potential of using unsupervised data analysis techniques for new media art and design, and (ii) to contrast the embedded intentions in the design of this specific installation to the actual outcomes of it, in terms of recorded participant behaviours. The data collected over the course of the installation amounted to over *one million frames* of motion capture and physiological data from over *800 individuals.*

In the following section we analyse the data acquired under (i) spatial analysis, (ii) physiological and kinematic analysis, and (iii) gestural analysis categories.

4.1 Spatial Analysis

The goal of the spatial analysis was to obtain an overview of how the motion capture data was spread spatially. We achieved this by using histogram images to represent the spread of data in both the X-Y (face-on) and Z-Y (side-on) planes. The histogram images were generated by (i) separating the coordinate space into a two dimensional grid and creating a corresponding array (where the row and column numbers corresponded to the centre coordinates of each grid element), (ii) summing up the number of times that hand coordinates appeared in each grid element, and (iii) plotting the array as an image to distinguish them in terms of different intensity values. To account for variations in hand position due to differences in where the participants were standing, we scaled all of the hand coordinates relative to the coordinates for the centre of the participant's body. Figure 3(a) shows the histogram generated for the frontal (X-Y) plane using the right hand coordinates for all data frames. it indicates that right hand motion was predominantly situated in a semi-circular pathway about the centre of the participant, corresponding to outstretched arm movement, pivoting at the shoulder.

When analysing the images for the side-on (Z-Y) plane, we observed little variation in depth, which showed that the movement predominantly occurred in the coronal plane. When comparing the left and right hand histogram images we observed that the spread of motion was much more restricted for the left hand, suggesting that *handedness* influenced how people interacted with the installation. By applying a lower threshold to the histogram values (for both hands), we created a scatter plot of the most common hand positions. We then used a mixture of Gaussian clustering algorithm to outline the overall use of the interaction space and regions where hand motion was most frequent (Fig. 3 (b)).



(a) (b)

Fig. 3. (a) Right-hand X-Y histogram image. (b) Mixture of Gaussian plot showing six regions where hand motion was most prevalent: horizontally outstretched (2 & 6), above the head (1), down by the thighs (3 & 5), and in front of the torso (4)

4.2 Physiological and Kinematic Analysis

From the motion capture data we were able to extract two temporal features of the hand movements, variation in velocity and variation in angle. Velocity was calculated as described in (2) and angle was calculated based on (4) using the X-Y coordinates of each hand relative to the centre of the hip.

Figure 4(a) provides a typical plot of the velocity profile for a single participant's right and left hands, over an eight second window. It shows a high degree of *synchrony* in the timing of the movements of the left hand and the movements of the right hand. Figure 4(b) shows the angle of each hand over the same time window. It reveals that although the movement timing was synchronous, the relative hand positions are either *in phase* or *out of phase*, corresponding to symmetrical and non-symmetrical movement.

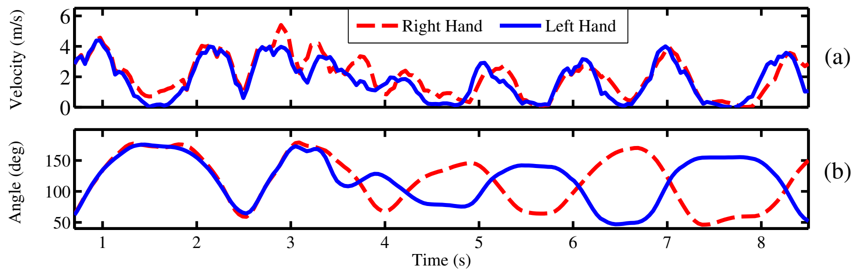


Fig. 4. Plots of right and left hand velocity (a) and angle (b) profiles for a single participant over an eight second window

We were also interested in exploring potential links between participants' behaviour and the content style they were interacting with. We separated the data according to which content style was active when it was recorded, then we compared averaged spatial, kinematic and physiological features of the data sets. The results for hand height (Y position), velocity and average heart rate are shown in Table 2. The hand data sample sizes were 104, 133 and 111 participants for the Wave, Spectrum, and Fire content styles respectively. This is less than the total number of participants because we only selected participants with at least one minute of data, using the first minute (1500 samples) for our analysis. The heart rate data sample sizes were 29, 42 and 34 due to discarding participants with intermittent readings.

These results suggest that participants interacting with the Spectrum content behaved more energetically, indicated by their higher average heart rate and hand velocity. However participants interacting with the Fire content had the highest average hand position. The latter result concurs with our selection criteria, which used hand height as a positive bias towards selection of the Fire content style.

Table 2. Average right hand (RH) motion and heart rate values separated by content style (standard deviation shown in parenthesis)

Content Style	RH height (m)	RH Velocity (m/s)	Heart Rate (bpm)
Wave	-0.09 (0.45)	1.49 (1.67)	94 (13)
Spectrum	-0.08 (0.42)	1.85 (1.83)	102 (13)
Fire	0.01 (0.43)	1.52 (1.50)	97 (17)

4.3 Gestural Analysis

In contrast to the numerically oriented analysis above, we also manually analysed the gestures which participants on the Mood Conductor performed. The intention in doing this was to create a descriptive library of the most common gestures. We achieved this by watching and annotating animated replays of the motion capture data. We gave names to ten of the most commonly observed gestures, these are described below and depicted visually in Fig. 5. The gestures are short in duration with a maximum of two movement phases - these are annotated by light/yellow arrows (first phase) and dark/red arrows (second phase).

1. **Propellers**: Both arms perform circular motions, either simultaneously or alternately. The direction of rotation is usually opposite for each arm, however this may be changeable.
2. **Sway**: Both arms perform a simultaneous left-right/right-left swaying motion above the head.
3. **Flag**: One extended arm performs an up/down flagging motion whilst the other arm is stationary at the participants side. This may also be performed as a single slow movement from the low to high position or vice versa.
4. **Seesaw**: Extended left and right hands move up and down simultaneously but in opposite directions.
5. **Hands Together**: Both hands are held together and circular motions are performed with extended arms.
6. **Angel**: Both extended arms move slowly up and down in synchrony.
7. **270°**: One arm moves through 270° in a circular path from the participants side to a horizontal position across the body. The other arm is stationary.
8. **Traffic Control**: One arm is extended vertically above the head and the other horizontally out to one side. Only one arm moves at a time, either the horizontal arm moves upwards to a vertical position or the vertical arm moves to a horizontal position.
9. **Wave**: Both arms perform a synchronous waving motion above the head, symmetrical about the sagittal plane.
10. **Wheel**: One arm moves in an extended and continuous circular motion, either clockwise or anticlockwise.

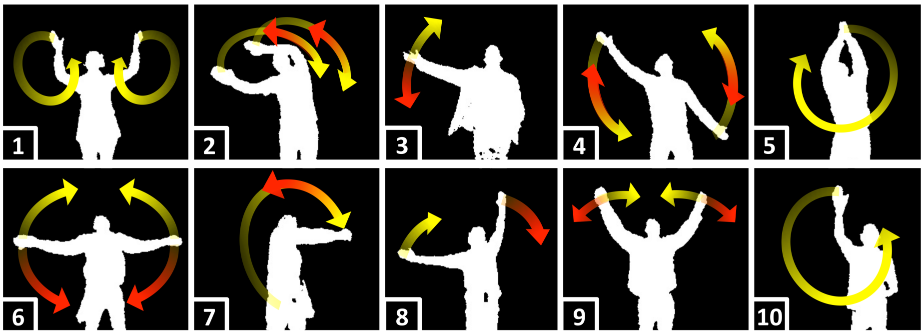


Fig. 5. Catalogue of ten of the most commonly observed gestures. Light/yellow and dark/red arrows indicate initial and secondary movement phases respectively

5 Discussion

How do people formulate an understanding of how to interact, and what gestures do they choose given the unfamiliarity of an interface? From his studies of interactive installations Wei [20] observed that the absence of rules often encourages participants to experiment and invent new meaningful gestures that are given significance by the corresponding changes in the experienced output - a process he termed *neosemy*. Our study attempted a detailed and data-driven investigation of how humans behave when confronted with such novel gesture-based interaction opportunities. By employing various methods of analysis we were able to describe and quantify this behaviour from different perspectives.

The spatial analysis showed that the majority of hand movements occurred along a circular pathway centred on the participants' torsos. It may seem trivial to conclude that this was related to the circular shape of the London Eye. However, it leads us to question the extent to which more complex shapes might influence the perceived interaction space in situations where the gestural interface allows free movement.

By plotting velocity and angle profiles for individual participants we were able to reveal and quantify certain kinematic features of the interaction. In particular we observed highly coordinated phase/anti-phase relationships between participants' left and right hands. This synchronised coupling of hand motion has been observed in previous studies [21]. It also relates to the notion of *movement qualities* - the characterisation of movements according to their temporal features (dynamics), independent of spatial trajectories and shapes [22]. There is certainly scope for further analysis in this area.

When coupling the kinematic results with the heart rate data, our findings suggested that people's average behaviour differed according to the content style they were interacting with. We found that participants interacting with the Spectrum content behaved differently to those interacting with the other two content styles. It is not possible to draw any definite conclusions as to why this was, however the Spectrum content did exhibit more colour variation than the other two content styles. Due to the limitations of collecting data in the wild, we were unable to obtain detailed and in-depth insight into this data, as we did not have access to subjective reports of mood from the participants.

In our analysis of common gestures we were surprised by the frequency at which gestures re-occurred between nights and participants, especially in the absence of any instruction as to how to interact with the installation. There are a number of features that are common to most of these gestures: (i) they tend to be performed in the coronal plane, potentially due to the fact that the main interaction control was also based upon movement in this plane, (ii) they are predominantly performed with extended arms and do not involve much movement of the body, and (iii) each gesture comprises relatively short and repeatable movements that exhibit high degrees of rhythm, synchrony and symmetry.

6 Conclusion

The London Eye Mood Conductor project allowed us to practically explore the intersection of human nonverbal behaviour research and new media art while providing the opportunity to collaborate with artists and design a novel installation which facilitated the collection of data in the *wild*. Consequently, we were able to demonstrate how a varied and quantitative analysis of such data can reveal potentially interesting aspects of human behaviour and affective expression in the context of interactions with new media art. The premise of the installation - to let people represent their mood by controlling the lights on the London Eye - meant that it was particularly amenable to such an investigation. Having said this, it could be argued that a desire to invoke nonverbal behaviour and affective engagement is inherent in the majority of interactive and new media artworks. Given the increasing prevalence of such works, there is a great opportunity for researchers and artists to engage in collaborative studies. For the artist, affective behaviour analysis techniques can facilitate the creation of artworks that are human-centred, where our reaction to the work is juxtaposed with the work's reaction to us. For the researcher, one of main advantages of these studies is the availability of large amounts of naturalistic data, which would be difficult to obtain in laboratory-based experiments. The results of our analysis showed that such data presents new challenges when it comes to the analysis and extraction of meaningful results. Tackling these challenges will be a necessary and important step in affective behaviour understanding *in the wild* for new media art applications.

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