Visualizing the Emotional Journey of a Museum

Shen DU, Edouard SHU, Feifei TONG, Yinghao GE, Lu LI, Jingbo QIU
Ecole Centrale de Lyon
36 Avenue Guy de Collongue,
69134 cully, France
first.name@ec-lyon.fr

Philippe GUILLOTEL, Julien FLEUREAU, Fabien DANIEAU
Technicolor
975, avenue des Champs Blancs, 35576
Cesson-Sevigne, France
first.name@technicolor.com

Daniel MULLER
Ecole Centrale de Lyon
36 Avenue Guy de Collongue,
69134 cully, France
daniel.muller@ec-lyon.fr

ABSTRACT

Wearable devices and new types of sensors make it possible to capture people behavior, activity and, potentially, cognitive state in their daily life. Today those devices are mainly used for well-being applications, by recording and displaying people's activity. Some work have been published going a step further by inferring from the recorded signals the emotional state of individuals or group of people. However, the information provided and the way it is presented are still in their infancy, with time lined graphs showing calories, heart-rate, steps, temperature, and sometimes affective intensity.

In this paper we present an experiment done during the visit of different people in a museum of arts to capture the emotional impact of the exposed paintings. We also propose an associated visualization of their emotional journey. The emotion is here measured as the affective response to the paintings observation, and the processing algorithm is based on an existing technique adapted to the particular case of different observation durations. The visualization is based on a 3D map of the museum with different colors associated to the different paintings to get the emotional heat-map of the museum (more precisely the arousal dimension). The validation has been done in the museum of arts at Lyon, France, with 46 visitors, for a total of 27 paintings, exposed in three different rooms.

Author Keywords

Emotion; Visualization; Physiological responses; Data processing; Museum; Art;

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

EmoVis 2016 Workshop, March 10, 2016, Sonoma, CA, USA.
Workshop proceedings published by Linköping University Electronic Press.

INTRODUCTION

Evaluating people experience means being able to evaluate engagement, emotions, pleasure, etc. Notions that by definition are difficult to express and measure. Traditionally self-assessment, helped with questions by professionals, is used and further analyzed by psychologists. For instance the Self-Assessment Manikin (SAM) [2] is widely used to measure the pleasure, arousal, and dominance associated with a person affective reaction. It is a non-verbal pictorial assessment technique to ease interpretation and coherence between different subjects. However, there are several bias and limitations that make such methods unusable for real applications where the subjects are experiencing different events in various locations and live conditions.

Recently, wearable devices to measure physiological responses have been made available, with corresponding signal processing and algorithms to infer affective reaction from those signals. The main advantage of this measure is its unconscious and objective nature. Three main signals have been used for emotion detection: the facial expressions [11], the body gestures [13], and some biological reactions from the autonomic nervous system, such as skin conductivity, heart rate, skin temperature [3] or pupillary response and eye blinking. Such methods have been experimented for various entertainment applications: music [5], movies and video [14], [4], [17], or advertisement [10]. However, there is not so much trials done for paintings. The most relevant is probably the eMotion mapping museum experience [16], [15]. Probably because art appreciation addresses deep cognitive information such as religion, culture, education, history, etc.

Besides how to capture emotional reactions, the second issue raised is how to represent them to reflect time (when it happened), space (where was the subject), intensity (how strong the emotion was), type (what was the valence of the emotion), and variability (how does it compare between individuals and different experiences). Interesting attempts have been proposed for well-being applications, especially with smartphones, such as the Moodscope [9], an online platform aimed at tracking ones mood throughout a certain period of time. In general the user is prompted to rank his feelings towards different emotional states, ideally on a daily basis. A simple 2D graph curve indexed by days is used to represent the mood score. MoodJam (`http://moodjam.com/`) adds patterns of colors and words to describe people mood and share it with others. Other similar apps have been proposed linked or not

to social networks, but the representation is still very simple, using only simple colored patterns or scales, representative of people's mood. It also requires the user to manually set his own feelings. Besides the bias of this interpretation, and the difficulty to associate words and colors to an emotion, it may not necessarily represents the truth. More complex representations have been proposed for music experiences by Krcadinac [6] and Kaushal Agrawal in Data Visualization Mood of the Artist (`http://www.kaushalagrawal.com/moodoftheartist.php`). The book Emotional Cartography by Christian Nold [12], provides an unique collection of essays discussing the desire to map emotions, by visualizing intimate biometric data and emotional experiences. It is a very relevant work providing *"a tangible vision of places as a dense multiplicity of personal sensations"*.
In this paper we want to answer two main questions: how to measure the quality of a museum experience? and how to visualize the resulting affective experience? For that we propose a new way to visualize the emotional experience, based on physiological responses induce by pieces of art (paintings in that case). In particular we provide a capture and playback system of the journey, highlighting the emotion intensity (arousal) for each painting. Different analytic visualization methods are also proposed to evaluate individuals, groups, rooms, and paintings specifically. The first part details the affective detection method and how values are extracted from the visitors' body responses. The second part describes the different representations used. Finally the third part provides the results of the experiments done with real visitors of the museum of arts of Lyon, France.

AFFECTIVE DETECTION

The affective responses have been captured using the "galvanic skin response" (GSR), also known as "skin conductance" or "electrodermal activity" (EDA). When an emotion is experienced, the autonomic nervous system activity causes a change in the skin's conductivity as a result of the activity of the sweat glands. This link between the GSR and the people emotional state was shown in various publications [8, 1, 7]. We have re-used this property and developed a dedicated algorithm to infer the emotional state from the GSR by means of the affective responses. This algorithm is detailed in this section.

Acquisition

First the affective responses have been captured using the BodyMedia Armband™ wearable sensor depicted in Figure 1 (`http://www.bodymedia.com/armband.html/`). The data rate was set to 32Hz, thus sample rate is $T = 1/32$. To keep only the relevant signal parts, i.e. the one when the visitor is watching a painting, we observed the visitors and annotated the start and end time when he was watching each painting. It allows us to remove noise due to motion between two paintings and to measure the observation duration for each painting. This observation duration is necessarily different for each visitor and each painting. By doing that way, all the observations can be synchronized for each painting and each visitor. Then, the raw data from the sensors are extracted for each observation time slot, the remaining data are removed.

Figure 1. Wearable sensor used. BodyMedia Armband™.

Those raw signals are then processed according to the next paragraph.

Processing

To compute the affective highlights from the raw GSR signal, the algorithm reported by Fleureau et al. [4] was used. However, this algorithm was developed for movie assessment, for which the observation duration is the same for all the observers. In our case we had to adapt the algorithm to this variability of duration, and also to the constraint that we want to compare the different exposition rooms against each other. The number of paintings per room being different, this second variability has also to be taken into account. It leads to the algorithm depicted in Figure 2, with the following successive steps:

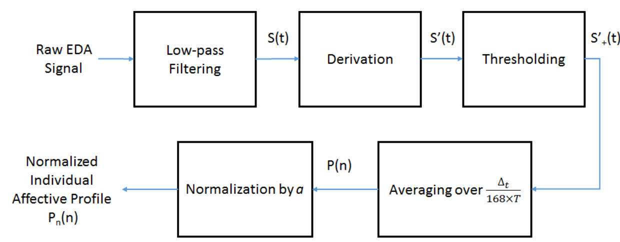


Figure 2. Description of the different steps of the algorithm to compute an Individual Affective Profile from the raw EDA.

- **Low-pass filter** : to remove noise and unnecessary information
- **Derivation** : only the GSR variations are relevant for the affective responses ([8])
- **Truncation with positive data** : to detect the phasic changes consisting in a fast increase until a maximum, followed by a slow return to the initial value
- **Elimination of unnecessary values** : to remove data out of the observation time
- **Averaging** : to handle the different observation duration between visitors
- **Normalization** : to be able to compare between paintings and observers
- **Histogram** : as a visualization of the result

The low pass filter is a FIR filter with a 2Hz cutoff frequency. The filtered values are then derivated and truncated to positive values $x(n)$ in order to highlight the relevant phasic changes according to [7]. After removing data out off the observation time interval, the signal is temporally filtered and subsampled using a variable time window based on the visitor observation duration $\Delta_t(x)$.

Averaging

Since all observers have different ways to observe the paintings, the integration interval time is adapted by fixing the number of observation samples N per room and observer. A reasonable number of observations per painting appeared to be ~ 20, leading to a total number between 140 and 240 per room. The minimum common multiplier for the number of paints per rooms being $7 \times 4 \times 3 \times 2 = 168$, $N = 168 \times T$ provides a sufficient resolution and accuracy. In addition, since the minimum observation time per individual and painting is around 4-5 s (based on our experiments), at least 6 to 8 raw samples are integrated to get an observation. Similarly, the average observation time is around 45-60 s, leading to 72 to 96 integrated raw samples. Therefore it provides a good filtering of the values and also a good accuracy regarding the slow phasic changes of the GSR (i.e. $\sim 2s$). Finally, it gives the same number of observations per viewer and per room, making comparisons easier. It also intrinsically takes into account the observation duration difference between paintings, as an emotional parameter. It can be assumed that the longer one watches a painting, the higher the impact is, compared to the other paintings.

It leads to affective measures $p(n)$ per individual for one room defined as:

$$p(n) = \frac{1}{N_x} \sum_{i=1}^{N_x} x(i+n) \tag{1}$$

where $N_x = \Delta_t(x)/N$ is the integration step, for a total observation duration Δ_t for observer x in a room.

Normalizing

Then, the individual affective profile $p_n(n)$ is obtained after normalization by the individual affective intensity a (computed to get the area under the curve equals to one). We assume there that $p(n)$ is analogous to the probability of an affective response at time n. It also removes the user-dependent part related to the amplitude of the GSR derivative which may vary from one subject to another.

The mean affective response $\overline{p_n}$ of an individual is given by the average value of the $p_n(n)$ values:

$$\overline{p_n} = \frac{1}{N} \sum_{i=1}^{N} p_n(i) \tag{2}$$

This whole process is illustrated in Figure 3 and Figure 4, for room "Religion" and 7 paintings. The raw signals $x(n)$ is illustrated in Figure 3, and the corresponding normalized individual affective profile $p_n(n)$ in Figure 4.

VISUALIZATION

The visualization is twofold, first a 3D model of the museum rooms is designed to map the emotional profiles (affective highlights) with the museum layout. Second the emotional

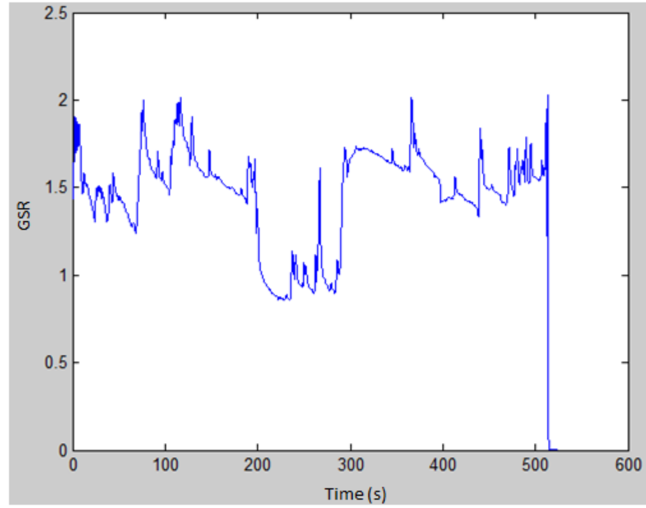


Figure 3. Captured individual raw GSR signal during the visit of one visitor for the 7 paintings of room "Religion".

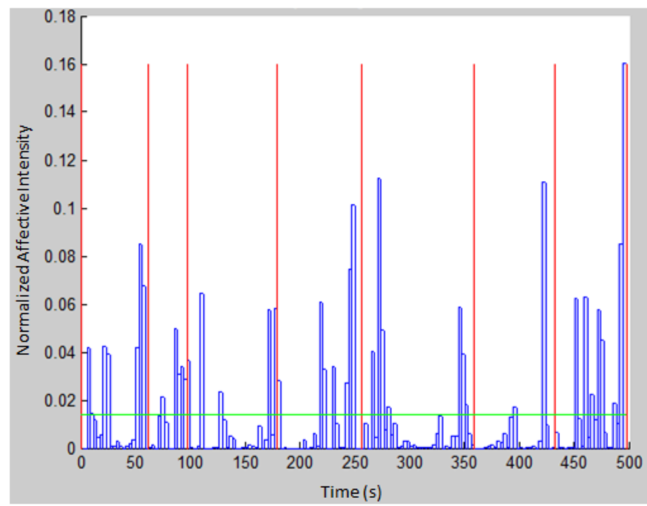


Figure 4. Individual affective response for the 7 paintings of room "Religion". Red lines are the separation between the different paintings, the green line is the average response $\overline{p_n}$ for this visitor.

profiles are represented by a color histogram associated to the paintings, and a wall color representing the average emotional intensity of the considered painting.

Museum 3D model

The museum rooms have been synthesized using a 3D design software (Trimble SketchUp, `https://www.sketchup.com/fr`). An point of view is provided in Figure 5. All the paintings are exposed as in the real museum. All the proportions are kept consistent with the originals.

Paintings emotional profiles

To represent the emotional profiles we have used an histogram with colors corresponding to a heat-map, where blue means low emotional intensity, and increasing intensity levels for the others colors, up to the red. Each bar corresponds to one visitor.

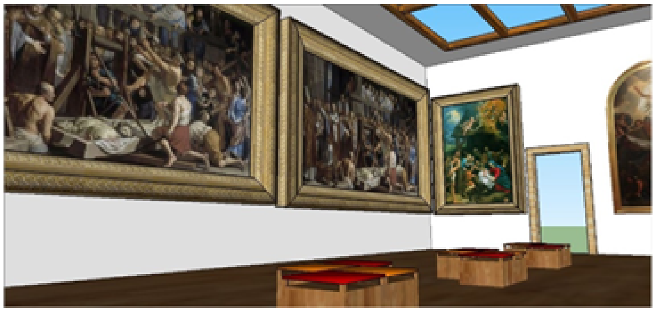


Figure 5. Example of the 3D model for room "Impressionists".

Museum heat-maps

The same color convention is used to color the wall and ground of the museum so as to directly identify the higher emotional areas. However the color is selected as the average intensity level over all observers (see Figure 11).

EXPERIMENTS

The previous algorithm has been used to process the data with a total of 46 visitors for 3 rooms: "Religion", "Impressionists" (aka Monet), and "Abstractionists" (aka Picasso). The capture has been done during several days at the Lyon museum of arts, taking volunteers at the entrance and following them to index the different start/end time at each painting. Each visitor has been tracked only in one room. The total number of paintings and observers per room is the following:

Room	Religion	Impressionists	Abstractionists
# Paintings	7	12	8
# Visitors	21	17	8

Table 1. Number of paintings and visitors per room.

Once captured, all the raw GSR signals have been uploaded and processed to compute the following different results and analytics.

Per individuals

The first analytic measure computed is the emotional profile of an individual in one room, i.e. how each participant responded in front of each painting. It is based on the average emotional response per painting computed as described in Section *"Processing"*. The corresponding values are given in Figure 6 and Figure 7 for two different visitors (visitors 7 and 17 respectively) when watching the 7 paintings of the room "Religion". Each bar corresponds to one painting and the amplitude is the affective intensity level. One can note the significant difference between the two observers. Visitor 7 is mostly sensitive to the last three paintings (painting 5 to 7), while visitor 17 is more responsive to paintings 3, 4 and 6. It means that each of them is impacted differently by the paintings depending of his history, education, feelings, belief, etc. However, thanks to these individual emotional profiles, we can compare the differences between rooms and paintings over a population, and even between observers.

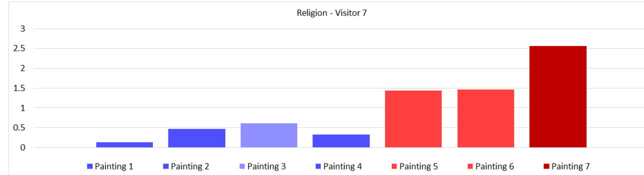


Figure 6. Resulting individual affective response of visitor 7, for the 7 paintings in room "Religion".

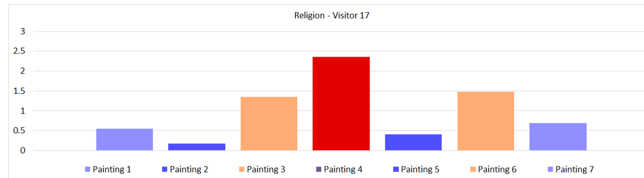


Figure 7. Resulting individual affective response of visitor 17, for the 7 paintings in room "Religion".

Per paintings

In addition to the individuals' responses, it would be interesting to compute the paintings profiles, i.e. what is the impact of a painting on visitors. It is computed as the average responses of the different observers for each painting. Figure 8 shows an example for one painting and 21 visitors. Once again the individuals variability is clearly visible, with visitors 4, 6, 7, 8, 10, 15, 21 as the most responsive, and visitors 2, 3, 5, 11, 12, 20 the less. Then, with these profiles it is possible to compare the different paintings. Figure 9 is another painting with the responses of the same 21 visitors. The second painting (painting 6) is clearly more impacting visitors

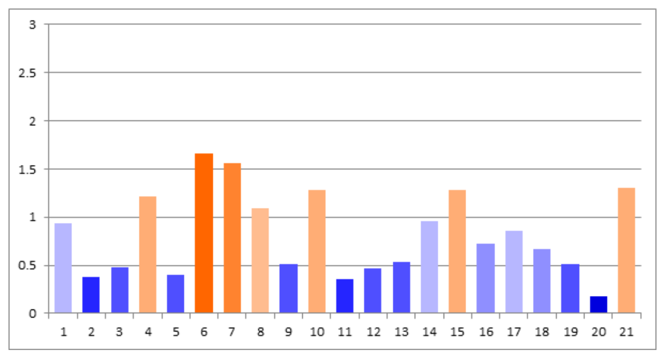


Figure 8. Resulting affective profile of painting 2, room "Religion".

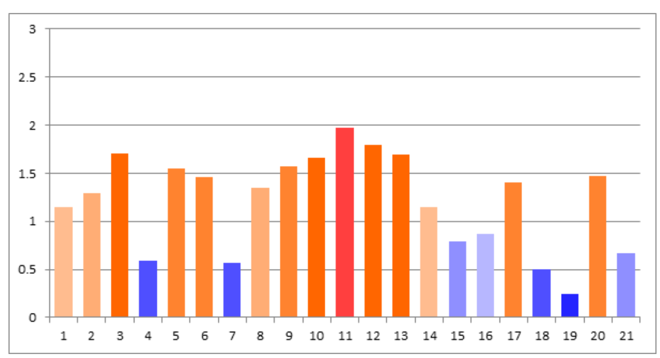


Figure 9. Resulting affective profile of painting 6, room "Religion".

than the first one (painting 2), with average intensity levels higher.
To have an idea of the corresponding paintings content the reader should refer to Figure 10 where the corresponding pictures are illustrated.
From these profiles, it is then possible to define a ranking for each painting. The 3 most higher mean affective responses $\overline{p_n}$ per painting and visitor are selected. Then the number of occurrences of each painting in this top 3 is computed to serve as ranking. This method has been preferred to the direct mean affective responses $\overline{p_n}$ to be able to take into account the high variability between observers. We assume that the three highest responses are the most significant whatever the differences. This ranking is given in Tables 2, 3, 4 for each room respectively under line *# Occurrences*. $\overline{p_n}$ is also included for comparison. *# Occurrences* is thus the number of visitors with this painting in their top 3 higher mean affective responses. When comparing Figure 8 and 9, we observe that painting 2 is lower than painting 6 on average. This is also reflected by the ranking where painting 2 is ranked 5 times in the top 3, while painting 6 is ranked 12 times in top 3 (the higher, the better). This is also confirmed by the $\overline{p_n}$ values with respectively 0.83 and 1.15. This is not always the case (see for instance painting 8 in room "Abstractionists") because top 3 may be more representative of *"interesting"* paintings that the direct mean affective arousal.

Room Religion							
# Painting	1	2	3	4	5	6	7
# Occurrences	4	5	11	5	6	12	7
$\overline{p_n}$	0.92	0.83	1.10	0.99	0.97	1.15	1.03

Table 2. Ranking for room "Religion" by means of the number of occurrences in top 3 highest responses and average affective intensity for all visitors.

Room Impressionists												
# Painting	1	2	3	4	5	6	7	8	9	10	11	12
# Occurrences	5	4	5	4	3	1	2	6	3	5	3	7
$\overline{p_n}$	0.99	0.87	0.88	0.99	0.81	0.89	0.90	1.22	0.812	1.26	1.04	1.33

Table 3. Ranking for room "Impressionists" by means of the number of occurrences in top 3 highest responses and average affective intensity for all visitors.

Room Abstractionists.								
# Painting	1	2	3	4	5	6	7	8
# Occurrences	3	1	2	2	2	2	1	1
$\overline{p_n}$	1.32	0.81	0.78	0.97	0.89	1.07	0.64	1.52

Table 4. Ranking for room "Abstractionists" by means of the number of occurrences in top 3 highest responses and average affective intensity for all visitors.

Once the *affective profile* of each painting computed it can be displayed on the 3D graphic model of the museum. We decided to add it bellow the paintings as described in Figure 10. On the same pictures, we also changed the color of the wall where the painting is displayed to reflect the mean $\overline{p_n}$ value over all visitors for each painting. The heat-map correspondence is used (blue is low, orange/yellow is medium, red is high). Therefore, when looking to a painting, the visitor directly access the average affective intensity and to a more detailed affective profile.

Figure 10. Emotional profiles visualization for painting 2 (left) and 6 (right), room "Religion".

Per rooms

Another way to represent the collected data is to compare the different rooms to each other. The first representation format used is the direct display of the visitors affective responses for each painting, and each room. It gives Figure 12, Figure 13 and Figure 14 for respectively room "Religion", room "Impressionists" and room "Abstractionists".

	Variance
Room Religion	0.11
Room Impressionists	0.18
Room Abstractionists	0.30

Table 5. Variance of the affective values for all paintings and visitors in each room.

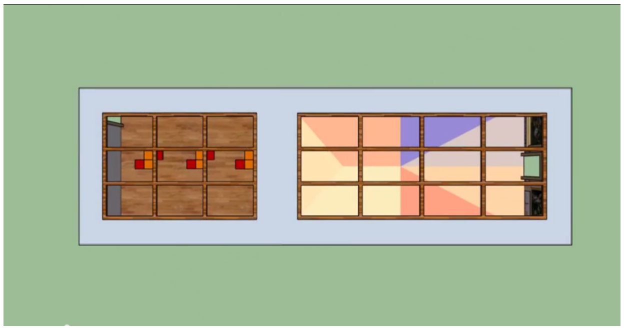
It allows a direct and complete comparison. For instance, room "Impressionists" is the one with the highest responses, and room "Abstractionists" the room with the highest variability. This is confirmed with the variance computed on all the paintings per room in Table 5.
The final representation depicted in Figure 11, uses the previous color mapping on the 3D model and extend it to the floor. Then, a global view of the museum rooms is easy, with the paintings "emotion profiles" depicted bellow the paintings, and the wall and ground colorized according to the painting mean emotional value. In addition, navigation is possible within the 3 rooms of the museum, to explore the paintings, and have an overview of the paintings with higher emotion intensity, lower intensity or higher variability. It would be particularly useful for the visitors to prepare their visit.

DISCUSSION

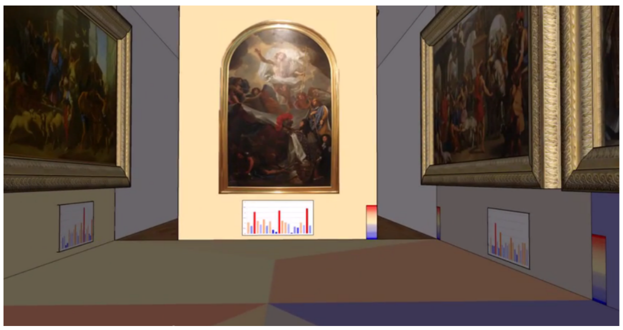
Based on the experiments and various discussions with the visitors, the results on the different rooms can be described as follows.

Room "Religion"

This room shows 7 religious paintings about the Christianity. Their size is larger than the other rooms, as well as their colorfulness. From our observations, it leads visitors to spend more time watching those paintings. In addition, a large part of the visitors are not Christians but rather from Asian culture which could also explain the rather low average responses. This is increased by the fact that all paintings are very similar in color and atmosphere, factors that usually may stimulate different reactions. Therefore, besides the richness of these magnificent paintings, the visitors responses are not very strong nor very weak, and relatively homogeneous between paintings as depicted in Figure 12, and confirmed by the variance in Table 5.



(a)



(b)

(c)

Figure 11. Screenshots of the final visualisation in the 3D model of the museum. (a) top view showing the ground color in front off each painting with the color representing the average intensity level. (b) inside front view of one painting with the affective profile bellow the painting and both the wall and ground color representing the average intensity level. (c) intermediate viewing angle.

Figure 15. Example of paintings. Left: room "Impressionists" *"Stormy Sea in Étretat"* by Claude Monet, 1883. Right: room "Religion" *"Le Repas chez Simon Le Pharisien"* by Jean-Baptiste Jouvenet, 1706.

An example of the paintings of this room is given in Figure 15, with the *"Le Repas chez Simon Le Pharisien"*,1706, by French painter Jean-Baptiste Jouvenet. It corresponds to painting number 6 in Figure 12.

Room "Impressionists"

Despite the highest number of paintings (12), this room is actually the smallest one. The different paintings are very small and similar to each other. Claude Monet is one of the exposed artist, and the paintings depict mainly landscapes and portraits. The mean observation duration per painting is lower in this room than in the two other rooms. It can be explained by the small size, the close distribution and relatively simple content. However we can extract three different behaviors, i) paintings 1 to 5 are similar, consisting of landscapes with bright colors, generally peaceful, ii) paintings 6 to 8 are dark, showing sad people, and iii) the remaining paintings with dense pictures colorful and textured. It may explain the high responses in paintings 7 and 8, and the relatively higher mean responses for paintings 10 to 12 in Figure 13. These different types of content also explain the higher variability shown in Table 5.
An example of the paintings of this room is given in Figure 15, with the *"Stormy Sea in Étretat"* an 1883 painting by founder of French impressionist Claude Monet. It corresponds to painting number 4 in Figure 13.

Room "Abstractionists"

This room exhibits abstractionist artworks that really encourage the imagination of visitors, even those without artistic expertise. Pablo Picasso is one of the exposed painter, and is the one that exhibits the higher responses (paintings 1 and 8). The content and style of the 8 paintings in this room are very different to each other. It explains the higher variability in the resulting affective values in Table 5. Not surprising, some paintings are difficult to understand (for instance paintings 3 to 5), since abstract work often requires background knowledge on the artist and his work. Anyway, in this room, there is a lot of elements that lead to a strong emotion (see Figure 14). However, it should be pointed out that as this room was a temporary exhibition, we have not been able to capture as many visitors as for the other two rooms.

CONCLUSION

We conducted an innovative experiment to visualize the journey of a person visiting a museum of arts. Based on the observer physiological responses (the GSR here) we computed the individual and average affective responses and provide the *"emotion profile"* of a painting, as well as the *"emotional map"* of the museum. The main advantage of this representation compared to state of the art, is that we do not try to interpret people reactions, which is very complicated and challenging. It implies psychology, art, education, culture, etc. Instead, we prefer to rely on people's nervous system response, which provides unconscious and objective responses. We observed a very high variability between visitors, but taking a population is more interesting and allows to compute the museum map. In addition, the proposed representation is a first step towards more advanced solutions and possible new ways to visit a museum (more interactive and emotionally selective). Further analysis with art experts and psychologists would be helpful to go further. In addition, comparisons of different museums would also be an interesting extension of this work. We also expect that this new way to represent a museum content or experience could be useful to define the museum strategy of placement, communicate on the expositions, as well as be an additional helpful information for the potential visitors.

ACKNOWLEDGMENTS

We thank the Lyon Museum of Fine Arts "Musée des Beaux-Arts" for their contribution to this work (`http://www.mba-lyon.fr/`), as well as the Ecole Centrale de Lyon (`www.ec-lyon.fr/`) for their support during this study.

REFERENCES

1. Boucsein, W. *Electrodermal Activity (Second Edition)*. Springer, 2012.
2. Bradley, M. M., and Lang, P. J. Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry 25* (1994), 49–59.
3. Fleureau, J., Guillotel, P., and Huynh-Thu, Q. Physiological-based affect event detector for entertainment video applications. *IEEE Trans. on Affective Computing 99*, PrePrints (2012).
4. Fleureau, J., Guillotel, P., and Orlac, I. Affective benchmarking of movies based on the physiological responses of a real audience. In *Proc. Affective Computing and Intelligent Interaction (ACII 2013)*, IEEE (2013), 73–78.
5. Koelstra, S., Mühl, C., Soleymani, M., Lee, J.-S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., and Patras, I. Deap: A database for emotion analysis ;using physiological signals. *IEEE Trans. on Affective Computing 3*, 1 (2012), 18–31.
6. Krcadinac, U., Jovanovic, J., Devedzic, V., and Pasquier, P. Textual affect communication and evocation using abstract generative visuals. *IEEE Trans. on Human-Machine Systems to appear* (2015).
7. Lajante, M., Droulers, O., Dondaine, T., and Amarantini, D. Opening the black box of electrodermal activity in consumer neuroscience research. *Journal of Neuroscience, Psychology, and Economics 5*, 4 (2012), 238–249.
8. Lang, P. The emotion probe. *American Psychologist 50*, 5 (1995), 372–385.
9. LiKamWa, R., Liu, Y., Lane, N. D., and Zhong, L. Moodscope: Building a mood sensor from smartphone usage patterns. In *Proc. 11th International Conference on Mobile Systems, Applications, and Services (MobiSys'13*, ACM (2013), 389–402.
10. McDuff, D., El Kaliouby, R., Cohn, J. F., and Picard, R. Predicting ad liking and purchase intent: Large-scale analysis of facial responses to ads. *IEEE Trans. on Affective Computing 11*, 4 (2012).
11. Pantic, M., and Rothkrantz, L. Automatic Analysis of Facial Expressions: The State of the Art. *IEEE PAMI 22*, 12 (2000), 1424–1445.
12. Raqs Media Collective, van de Drift, M., Davis, S. B., van Kranenburg, R., Hope, S., and Stafford, T. *Emotional Cartography - Technologies of the Self*. Nold, Christian, 2009.
13. Saha, S., Datta, S., Konar, A., and Janarthanan, R. A study on emotion recognition from body gestures using kinect sensor. In *Proc. International Conference on Communications and Signal Processing (ICCSP 2014)*, IEEE (2014), 56–60.
14. Soleymani, M., Pantic, M., and Pun, T. Multi-modal emotion recognition in response to videos. *IEEE Trans. on Affective Computing 3*, 2 (2011), 211–223.
15. Tröndle, M., and Tschacher, W. The physiology of phenomenology: The effects of artworks. *Journal of Empirical Studies of the Arts 30*, 1 (2012), 79–117.
16. Tschacher, W., Kirchberg, V., van den Berg, K., Greenwood, S., Wintzerith, S., and Tröndle, M. Physiological correlates of aesthetic perception of artworks in a museum. *Psychology of Aesthetics, Creativity, and the Arts 6*, 1 (2012), 96–103.
17. Wang, S., and Ji, Q. Video affective content analysis: A survey of state-of-the-art methods. *IEEE Trans. on Affective Computing 6*, 4 (2015), 410–430.

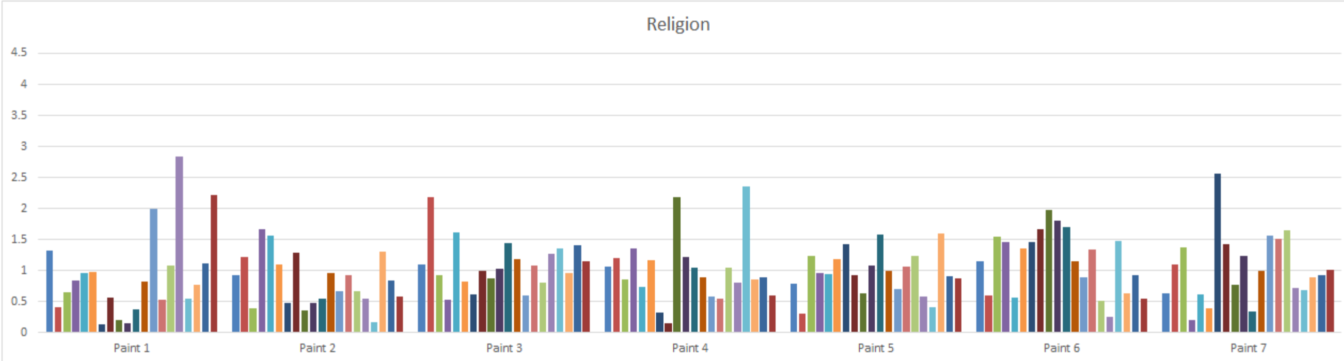


Figure 12. Emotional profiles of all 7 paintings in room "Religion" for the 21 visitors.

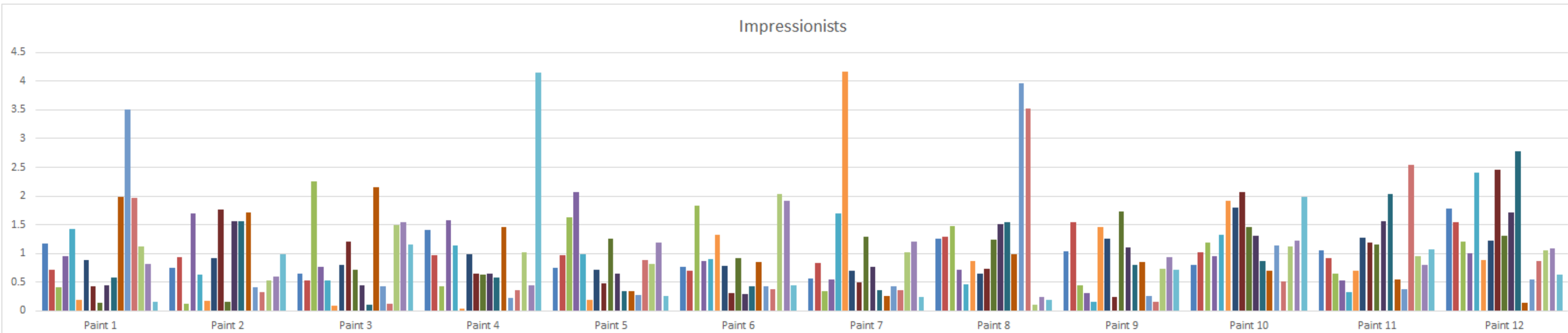


Figure 13. Emotional profiles of all 12 paintings in room "Impressionists" for the 17 visitors.

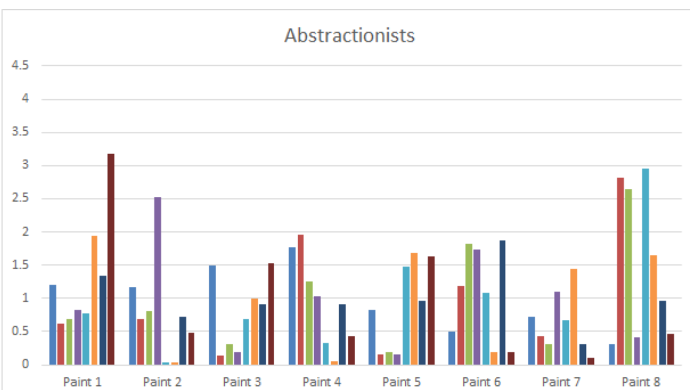


Figure 14. Emotional profiles of all 8 paintings in room "Abstractionists" for the 8 visitors.

Representation of the affective profiles for all visitors, all paintings and the three rooms respectively. Each bar corresponds to one visitor affective response, and the same color is used for one visitor between each painting in a room.