Two Dimensional Shapes for Emotional Interfaces: Assessing the Influence of Angles, Curvature, Symmetry and Movement

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***Abstract*—Recent investigations aiming to identify which are the most influential parameters of graphical representations on human emotion have presented mixed results. In this study, we manipulated four emotionally relevant geometric and kinematic characteristics of non symbolic bidimensional shapes and animations, and evaluated their specific influence in the affective state of human observers. The controlled modification of basic geometric and cinematic features of such shapes (i.e., angles, curvature, symmetry and motion) led to the generation of a variety of forms and animations that elicited significantly different self-reported affective states in the axes of valence and arousal. Curved shapes evoked more positive and less arousing emotional states than edgy shapes, while figures translating slowly were perceived as less arousing and more positive than those translating fast. In addition, we found significant interactions between angles and curvature factors both in the valence and the arousal scales. Our results constitute a direct proof of the efficacy of abstract, non-symbolic shapes and animations to evoke emotion in a parameterized way, and can be generalized for the development of real-time, emotionally aware user interfaces.**

Keywords–Affective Computing; Emotional interfaces; Graphical User Interfaces; Emotional Design; Expressive Interfaces.

I. INTRODUCTION

In the recent years, several efforts have been made in the field of Human Computer Interaction (HCI) to design and implement computer systems that can recognize and express emotion. A number of models have been developed to interpret physiological measurements [1], or behavioural records of body and facial expression in real time [2], and today, reliable ways of monitoring users emotions are being incorporated in commercial systems, such as Microsoft Kinect. On the other hand, models for the expression of emotion — which are usually based on psychological research — have been shown to coherently convey emotion to humans by manipulating human-like or anthropomorphic emotional stimuli. Specifically in the field of Computer Graphics, models for the synthetic expression of emotion using Computer Generated Imagery (CGI) have traditionally involved the use of so called avatars, i.e., virtual characters that simulate human facial expression [3][4], or body movement [5][6], to express a particular emotion explicitly (for a review see [7]).

However, it is well known that humans not only respond to human-like or symbolic emotional stimuli. In the literature on music and emotion, for instance, it has been shown that musical parameters such as tempo, pitch or tonality may profoundly affect a person's affective state [8][9][10]. Since most of the interactive systems with which we interact today present bidimensional user interfaces that are non-symbolic / non-anthropomorphic, it is relevant to identify what are the most important graphical parameters of emotion in simple forms and animations that can be used to generate such interfaces. Furthermore, the advent of new communication technologies allows today for the real time generation of highly parameterized CGI which offers great possibilities for the design and implementation of emotionally aware user interfaces. How can we identify the geometrical and cinematic properties of 2D shapes and animations that have more impact on emotion, and make use of this knowledge in the design of affective HCI systems?

Based on literature presented in Section II, we defined an experimental setup to investigate this question by assessing the influence of four specific graphical parameters of shapes and animations on emotion: angles, curvature, symmetry and speed of movement (Section III). Our results show that it is possible to experimentally induce emotional states in controlled environments by parametrically tampering these geometric and kinematic characteristics. The specific impact of each one of them is discussed in Section IV. In Section V, we present our conclusions and future work.

II. SHAPE, MOVEMENT AND EMOTION

A. Shape

The relationship between non symbolic graphic features and emotion has been studied from different perspectives. One approach mostly adopted in the Image Retrieval field has been to study global image features and assess their effectiveness in conveying specific emotions. Several parameters of color (i.e., hue, brightness or saturation [11]), and textures (i.e., coarseness, contrast and directionality [12]), have been shown to influence the affective states of human observers. Similar parameters have been identified in saliency-based visual models (i.e., colour, intensity, orientation and symmetry [13][14]) which can predict human fixations, although, to our knowledge, the relationship between saliency and emotion models has not been studied.

A problem with the study of complex images and global features is the great amount of dimensions in which such stimuli can be parameterized. Real images usually involve semantic components that can be highly influential on human emotion. Traditional databases for emotion induction, such as the International Affective Picture System (IAPS) [15] do not differentiate between symbolic and non symbolic emotion determinants, which makes them not suitable to assess the specific role of these two key elements. Some efforts, however, have been made to achieve this goal [16].

A different approach has been taken in the field of visual perception, where the synthetic generation of visual stimuli has been adopted in early studies. The seminal work of Attneave with bidimensional abstract shapes already showed that the parametric variation in basic geometric characteristics of such figures — number of turns in the contour, symmetry and angles — evoked completely different subjective judgements about their “complexity" [17][18].

A complexity scale was also used to rate shapes in [19] and [20], although the concept was defined in different ways — reproduction performance for the former and difficulty in providing a verbal description of an image for the latter. The variables that were considered more influential on the perceived complexity of a shape in both studies were orientation, repetitiveness and variance in interior angles.

Can such parameters be influential on emotion? The literature on the topic is sparse. Some studies have shown that curved shapes are better in portraying emotion than shapes composed by straight lines [21], and that features such as angles ratio, curvature and symmetry [22][23], can predict the emotion induced by specific 3D shapes. Other studies have proposed that the perceived emotion of abstract figures is determined by internal dynamics such as the subjectively judged “instability" of a figure. The intensity of emotions that can be ascribed to the figures is correlated with their perceived instability, which is defined by the figure orientation with respect to a predefined ground [24].

B. Movement

The relevance of movement in the expression of emotion has been highlighted in several studies, most of which have focused in human — or anthropomorphic — body motion. It has been argued that exaggerated corporal motion enables the recognition of the intensity of the affective states that can be attributed to body postures, and that parameters that define a specific body configuration can be correlated with the emotion attributed to it [6]. Moreover, it has been shown that speed and spatial amplitude play a fundamental role in emotional perception of human-like body movement [25]. Several studies on human body motion using point lights show that perceivers are able to infer emotions reliably and easily basing their judgments solely on the dynamic patterns of actions [26][27].

Abstract motion has also been studied, but in the same way that abstract figures have captured less attention than figurative graphical representations, the influence of non-articulated motion on human perception is less understood than its symbolic counterpart. Early studies already showed that emotional descriptions can be attributed to abstract figures that move in a non articulated, non anthropomorphic way [28][29]. In the same line, it has been suggested that the perception of animacy of a shape can be predicted by the magnitude of the speed change and the change of direction measured in angles [30][31] among other parameters. What are the features of abstract movement that most influence emotion? Density (animated notches of the contour), strength (amplitude in the deformation or translation), and speed were described as the most determinant factors of the emotion elicited by abstract shapes [25]. On the other hand, speed in the motion of abstract patterns has been shown to be highly influential on human emotion and behaviour in a mixed reality setup [32].

III. Methods

A. Description

The methodology and overall design of our experiment was based on a previous study conducted in our laboratory [33].

Different visual samples varying among two visual determinants of emotion (shape and movement) were presented to the participants. The morphological features that were considered — lines/curves ratio, acute/obtuse angles ratio, and symmetry — were extracted from [22] and [23], and adapted to our specific setup. Such parameters were the only geometrical features of shapes studied with respect to emotion that we found in the literature. Each one of these geometrical parameters was tested at three different levels of movement: low, medium and high (L/M/H). In total, 81 animations were rendered (i.e., 27 shapes at 3 different levels of movement each). The parameters that were manipulated are described in the following paragraphs.

1) Lines/Curves ratio: The Lines/Curves ratio (LCR) was calculated according to the following formula:

$$\mathrm{LCR} = \frac{\mathrm{Lines}}{\mathrm{Curves} + \mathrm{Lines}} \tag{1}$$

A low LCR was considered under $\frac{1}{3}$, medium between $\frac{1}{3}$ and $\frac{2}{3}$ and high between $\frac{2}{3}$ and 1.

2) Acute/Obtuse angles ratio: The Acute/Obtuse angles ratio (AOAR) was calculated according to the following formula:

$$\mathrm{AOAR} = \frac{\text{Acute angles}}{\text{Acute angles} + \text{Obtuse angles}} \tag{2}$$

A low AOAR was considered under $\frac{1}{3}$, a medium AOAR between $\frac{1}{3}$ and $\frac{2}{3}$ and a high AOAR between $\frac{2}{3}$ and 1. AOAR was also considered for curved shapes by counting the angles formed by correspondent tangents of adjacent curves. Reflex angles (between 180 and 360 degrees), were not considered in the equation.

3) Simmetry: Symmetry (SYM) was considered in 2 axes. A symmetrical figure among two axes was given a high level of symmetry; a symmetrical figure among one axe was considered at a medium level of symmetry, and a non symmetric figure was given a low level of symmetry.

4) Movement: All shapes were rendered in three different levels of movement (MOV): low, medium, high. In the low level, the image of the shape was rendered statically. In the medium and high level, movement was produced by translating the shape in pseudo-random directions, determined by a perlin noise algorithm. In the medium level, the range of translation was set to 5 VR units and the speed of translation of the algorithm set to 1. In the high level of movement, the range of movement was also 5, but the speed of translation was 5 times faster than the medium level.

5) Examples: A circle has a high symmetry, low lines curves ratio, and low acute obtuse angles ratio. An example of a figure that has high symmetry, high LCR and high AOAR is a star (for more examples see Figure 1).

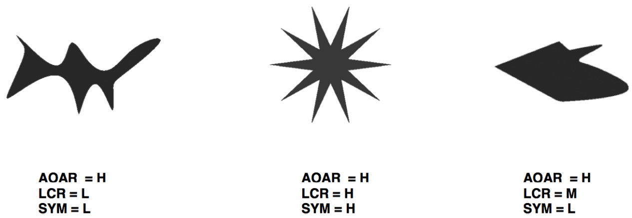

Figure 1. Abstract shapes used in our experiment. Left: high AOAR, low SYM and low LCR. Center: high AOAR, high LCR, high SYM. Right: high AOAR, medium LCR and low SYM.

B. Experimental Procedure

Our experimental design included four independent variables (LCR, AOAR, SYM, MOV) with three levels each (Low, Medium, High), and two dependent variables (arousal, valence) — the participants ratings in a nine points self-assessment scale (the self-assessment manikin [34], based in Rusell's circumplex model of emotions [35]).

Stimuli were presented in a randomized order. After eight seconds of exposure, participants were asked to rate the shape in the SAM scale while the stimulus remained visible. Precise instructions were given to them in order to assess their emotional states as it was at the moment of exposure. After the self-assessment has been achieved, an in-between period of eight seconds with no visual stimulation (black screen) preceded the next trial. Exposure time was made two seconds longer than the original self assessment study conducted with images [34] to allow a good exposure to moving images (animations). An application was developed for the generation and rendering of the stimuli and the online recording of the participant's responses using the Unity3D Game Engine.

C. Participants

A total of 12 university students (5 women, MAge = 28.333, range = 22-39) participated in the experiment. All of them had normal or corrected-to-normal vision.

IV. Results

A. Graphic representations

We carried a Two-Way Repeated Measure Multivariate Analysis of Variance (MANOVA), followed by univariate analysis and post hocs. Kolmogorov-Smirnov and Shapiro Wilk tests showed that the data was not normally distributed in valence and arousal scales; therefore, we run Kruskal-Wallis tests in the univariate analysis to verify the results.

1) Valence: In the valence scale, shapes composed mostly by curves were perceived significantly more positively than shapes composed by similar numbers of lines and curves. Shapes composed mostly by curves were also perceived more positively than shapes composed mostly by lines, although this difference was not significant. The analysis showed a significant multivariate effect for LCR $F(2, 9)$ ($p < 0.05$). Follow-up univariate analysis revealed an effect of LCR on valence $F(1.322,26,717) = 6.882$ ($p < 0.05$). Mauchly tests

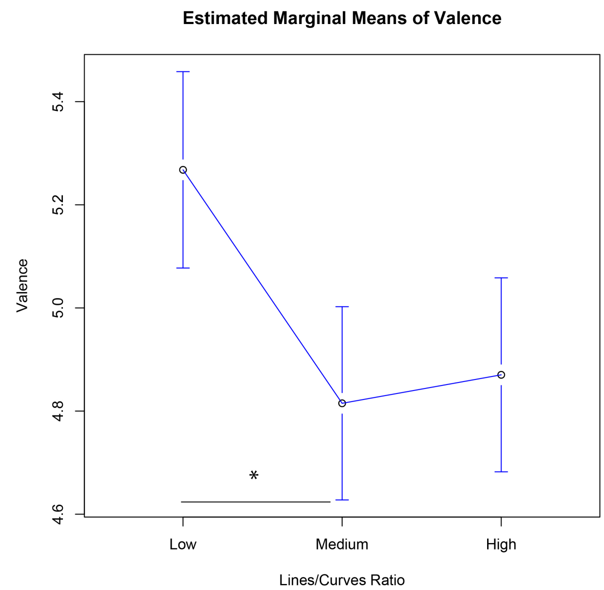

Figure 2. A figure composed mostly with curves is perceived significantly more positive than a figure composed by curves and lines.

indicated that the assumption of sphericity was not met. Hence we corrected the F-ratios with Greenhouse-Geisser. A post-hoc pairwise comparison with Bonferroni correction showed a significant mean difference of 0.4527 between Low and Medium LCR on the valence scale (Figure 2).

Besides, a significant interaction was found between AOAR and LCR for valence $F(4, 40) = 6{,}444$ ($p < 0.05$), suggesting than shapes composed mostly by acute angles — e.g., a star — are perceived more positive when they are also composed by straight lines. The analysis on valence also revealed a significant interaction effect in the multivariate analysis for the AOAR*SYM interaction $F(4,7)$ ($p < 0.05$), and for the LCR*SYM interaction $F(4, 7)$ ($p < 0.05$). When a shape is symmetrical in two axes, the presence of acute angles is perceived more positive. On the other hand, when the figure is asymmetrical, it will be perceived as more positive if it is composed mostly by curves.

2) Arousal: In the arousal Scale, the only significant multivariate effect was found for the interaction between LCR and AOAR $F(4, 7)$ ($p < 0.05$), and univariate analysis confirmed this result $F(4, 40) = 4.694$ ($p < 0.05$). When a shape has High AOAR, it tends to be perceived as more arousing if it also has a high LCR.

B. Movement

1) Valence: No significant multivariate effect was found for movement on valence. However, influence of movement on valence was reported by univariate analysis $F(1.633,143.265) = 5.969$ ($p < 0.05$) (Figure 3).

A post-hoc pairwise comparison with Bonferroni correction showed a significant mean difference of -1.1023 between Medium and High. Therefore, figures that moved slowly were perceived as significantly more positive that figures translating fast.

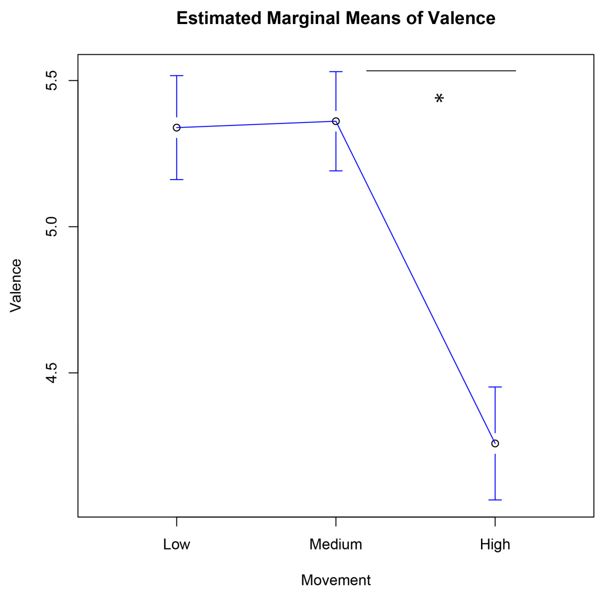

Figure 3. Different kinds of movement elicited different reports in the valence scale. Fast moving shapes were considered significantly less positive than shapes that moved slow and non-moving shapes.

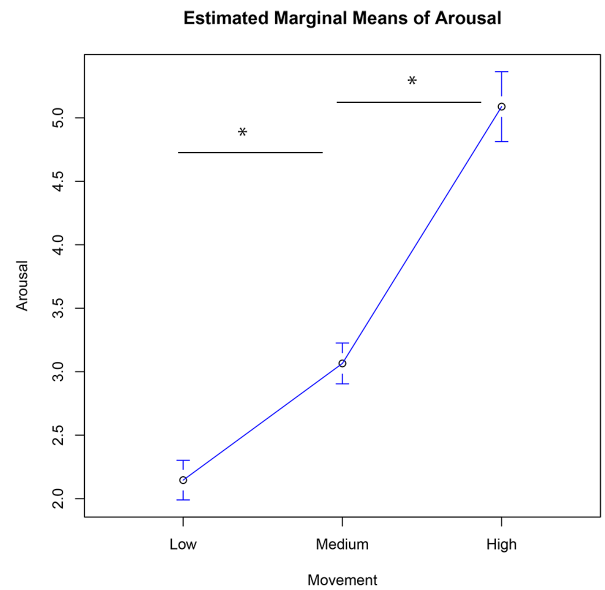

Figure 4. Movement significanlty affected the participants reports in the arousal scale. Fast moving shapes were considered significantly more arousing than shapes that moved slow and non-moving shapes.

2) Arousal: Movement was found to be highly influential in on arousal. Moving shapes were perceived significantly more arousing than non-moving shapes, and fast-moving figures were reported to be significantly more arousing than slowly-moving figures (Figure 4). The analysis showed a significant multivariate effect for movement $F(2, 9)$ ($p < 0.05$) on arousal. Mauchly tests indicated that the assumption of sphericity was met. Therefore, we did not correct the F-ratios for the following ANOVAS. Follow-up univariate analysis revealed an effect of movement $F(1.112, 1232.994) = 20.715$ ($p < 0.05$) on arousal. A post-hoc pairwise comparison with Bonferroni correction showed a significant mean difference of -0.9195 between Low and Medium movement, of -2.0231 between Medium and High movement, and of -2.9427 between Low and High movement (Figure 4). In our design, Low was defined as absence of movement, and Medium and High were defined as different levels of speed in random translation.

V. Conclusions

Abstract shapes and animations varying among four emotionally relevant graphical parameters (i.e., proportion of lines and curves, proportion of acute and obtuse angles, symmetry and movement), were presented to the participants of our experiment and the correspondent emotional responses were recorded using self-reports based in the circumplex model of affect. Our results show that the manipulation of such low level graphical parameters evoked different affective states in our participants, and that some of them (i.e., LCR and movement) had a specific influence in the valence and arousal scales. In some cases, the interaction between parameters was significant (e.g., for curvature and angles in both the valence and arousal scales). Our results are a contribution to the understanding of the role that basic geometric characteristics of abstract, bidimensional shapes play on human emotion, and may be useful for developers and designers wishing to develop and implement emotional user interfaces.

We speculate that the manipulation of these parameters in real time and in less controlled experimental conditions will coherently influence the affective states of humans observers in a similar manner than observed in our experiment, and plan to reformulate our experimental design in order to include the real time generation of the stimuli from the identified parameters. We also plan to include more objective measurements of emotion such physiological records — i.e., Electrodermal Activity, Hear Rate, Respiration —, as a complement to the self-assessment responses. Such physiological data could be used in a second stage as an input to the system, allowing for the controlled generation of the stimuli depending on the users emotional states, and the development of more sophisticated, emotionally aware user interfaces.

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References

[1] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang, "A survey of affect recognition methods: Audio, visual, and spontaneous expressions," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 31, no. 1, 2009, pp. 39–58.

[2] M. Thrasher, M. D. Van der Zwaag, N. Bianchi-Berthouze, and J. H. Westerink, "Mood recognition based on upper body posture and movement features," in Affective Computing and Intelligent Interaction. Springer, 2011, pp. 377–386.

[3] P. Weyers, A. Mühlberger, C. Hefele, and P. Pauli, "Electromyographic responses to static and dynamic avatar emotional facial expressions," Psychophysiology, vol. 43, no. 5, 2006, pp. 450–453.

[4] A. Tinwell, M. Grimshaw, D. A. Nabi, and A. Williams, "Facial expression of emotion and perception of the uncanny valley in virtual characters," Computers in Human Behavior, vol. 27, no. 2, 2011, pp. 741–749.

[5] M. Fabri, D. J. Moore, and D. J. Hobbs, "The emotional avatar: non-verbal communication between inhabitants of collaborative virtual environments," in Gesture-Based Communication in Human-Computer Interaction. Springer, 1999, pp. 269–273.

[6] M. Inderbitzin, A. Valjamae, J. M. B. Calvo, P. F. Verschure, and U. Bernardet, "Expression of emotional states during locomotion based on canonical parameters," in Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 IEEE International Conference on. IEEE, 2011, pp. 809–814.

[7] V. Vinayagamoorthy, M. Gillies, A. Steed, E. Tanguy, X. Pan, C. Loscos, M. Slater et al., "Building expression into virtual characters," 2006.

[8] L.-L. Balkwill and W. F. Thompson, "A cross-cultural investigation of the perception of emotion in music: Psychophysical and cultural cues," Music perception, 1999, pp. 43–64.

[9] P. N. Juslin and J. A. Sloboda, Music and emotion: Theory and research. Oxford University Press, 2001.

[10] A. Goldstein, "Thrills in response to music and other stimuli." Physiological Psychology, 1980.

[11] P. Valdez and A. Mehrabian, "Effects of color on emotions." Journal of Experimental Psychology: General, vol. 123, no. 4, 1994, p. 394.

[12] H. Tamura, S. Mori, and T. Yamawaki, "Textural features corresponding to visual perception," Systems, Man and Cybernetics, IEEE Transactions on, vol. 8, no. 6, 1978, pp. 460–473.

[13] G. Kootstra, A. Nederveen, and B. De Boer, "Paying attention to symmetry," in Proceedings of the British Machine Vision Conference (BMVC2008). The British Machine Vision Association and Society for Pattern Recognition, 2008, pp. 1115–1125.

[14] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 20, no. 11, 1998, pp. 1254–1259.

[15] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, "International affective picture system (iaps): Technical manual and affective ratings," 1999.

[16] N. Liu, E. Dellandréa, B. Tellez, and L. Chen, "Associating textual features with visual ones to improve affective image classification," in Affective Computing and Intelligent Interaction. Springer, 2011, pp. 195–204.

[17] F. Attneave, "Some informational aspects of visual perception." Psychological review, vol. 61, no. 3, 1954, p. 183.

[18] F. Attneave, "Physical determinants of the judged complexity of shapes." Journal of Experimental Psychology, vol. 53, no. 4, 1957, p. 221.

[19] C. M. Mavrides and D. Brown, "Discrimination and reproduction of patterns: Feature measures and constraint redundancy as predictors," Perception & Psychophysics, vol. 6, no. 5, 1969, pp. 276–280.

[20] C. Heaps and S. Handel, "Similarity and features of natural textures." Journal of Experimental Psychology: Human Perception and Performance, vol. 25, no. 2, 1999, p. 299.

[21] R. Hiraga, "Emotion recognition in polygons and curved shapes," in Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference on. IEEE, 2011, pp. 3286–3291.

[22] S. Achiche and S. Ahmed, "Mapping shape geometry and emotions using fuzzy logic," in Proceedings of IDETC/CIE, 2008.

[23] S. Achiche and S. Ahmed-Kristensen, "Genetic fuzzy modeling of user perception of three-dimensional shapes," Artificial Intelligence for Engineering Design, Analysis and Manufacturing, vol. 25, no. 1, 2011, pp. 93–107.

[24] M. Pavlova and A. Sokolov, "Perceived dynamics of static images enables emotional attribution," Perception-London, vol. 34, no. 9, 2005, p. 1107.

[25] K. Amaya, A. Bruderlin, and T. Calvert, "Emotion from motion," in Graphics interface, vol. 96. Citeseer, 1996, pp. 222–229.

[26] A. P. Atkinson, W. H. Dittrich, A. J. Gemmell, A. W. Young et al., "Emotion perception from dynamic and static body expressions in point-light and full-light displays," PERCEPTION-LONDON, vol. 33, 2004, pp. 717–746.

[27] W. H. Dittrich, T. Troscianko, S. E. Lea, and D. Morgan, "Perception of emotion from dynamic point-light displays represented in dance," Perception-London, vol. 25, no. 6, 1996, pp. 727–738.

[28] F. Heider and M. Simmel, "An experimental study of apparent behavior," The American Journal of Psychology, vol. 57, no. 2, 1944, pp. 243–259.

[29] A. Michotte, "The perception of causality." 1963.

[30] P. D. Tremoulet, J. Feldman et al., "Perception of animacy from the motion of a single object," PERCEPTION-LONDON-, vol. 29, no. 8, 2000, pp. 943–952.

[31] B. J. Scholl and P. D. Tremoulet, "Perceptual causality and animacy," Trends in cognitive sciences, vol. 4, no. 8, 2000, pp. 299–309.

[32] A. Betella, M. Inderbitzin, U. Bernardet, and P. F. Verschure, "Non-anthropomorphic expression of affective states through parametrized abstract motifs," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on. IEEE, 2013, pp. 435–441.

[33] S. Le Groux and P. F. Verschure, "Subjective emotional responses to musical structure, expression and timbre features: A synthetic approach," 9th International Symposium on Computer Music Modelling and Retrieval (CMMR), 2012.

[34] M. M. Bradley and P. J. Lang, "Measuring emotion: the self-assessment manikin and the semantic differential," Journal of behavior therapy and experimental psychiatry, vol. 25, no. 1, 1994, pp. 49–59.

[35] J. A. Russell, "A circumplex model of affect." Journal of personality and social psychology, vol. 39, no. 6, 1980, p. 1161.