A Dynamic Approach for the Generation of Perceptual Associations

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Abstract

We propose a dynamic approach and computational artefact for the generation of cross-modal associations between the domains of visual communication and perception of emotions. This is accomplished by applying three key steps: (i) assemble an alphabet (ii), define a shape grammar, and (iii) generate computationally a dynamic representation for the previous point. We restrain the visual expression to a line movement and limit our set of emotions to four in order to establish an initial solid baseline of experiments. Experiments were done to assess the validity of the established associations between emotions and visual features. Results have confirmed some associations previously suggested by literature and have emphasized others. This approach may be a key aspect to solve problems of multi-domain contexts where non-verbal communication is required to connect two or more domains, e.g. visual arts, artistic performances, non-verbal languages, and entertainment.

Introduction

Emotions are shared among humans and transversal to several contexts and situations of our daily lives. They have been quite a popular means to mediate findings from distinct domains of knowledge (Lindborg and Friberg 2015; Pesek et al. 2017). Based on theoretical and practical evidence, we suggest that crossing perceptual and cognitive findings with several aspects of images (shape, size, etc.) may bring an additional value to a non-verbal communication and computational generation of multi-modal associations. To asses this, we develop a solution based on three-step key concepts: gather a multidisciplinary alphabet, define a shape grammar, and develop a computational solution.

The use of computational tools to explore multi-modal associations has been a topic of growing interest. This can be justified by the computers capacity to interpret and evolve abstract concepts with a certain degree of autonomy and abstraction (Boden and Edmonds 2009; Noll 1966; Moroni and others 2014; Sims 1992). Still, it remains a challenge in combining empirical knowledge and computational setups to create configurations with a certain degree of creativity and plasticity (McCormack et al. 2009).

Regarding the set of emotions used for this project, we decided to restrain our experiment setup to four emotions: anger, calm, happy, and sad the four extremes of the two-dimensional model of emotions (Russell 1980).

We defined as well set of rules to unambiguously guide a visual representation of these - in this stage of work we restrained this to visual expression of a line movement as it is a strong element of expression in any visual composition. We founded our computational language in shape grammars' knowledge. A shape grammar is a set of rules and geometric transformations that represent pre-defined rules. As (Stiny 1980) describes, a shape grammar *(SG)* is a 4- tuple *"sg = (vt,vn,r,i)* in which (i) *vt*: a set of terminal symbols; (ii) vn: a set of non terminal symbols; (iii) *r*: a finite set of ordered pairs whereas a shape consisting of an element of *vt* is combined with an element of *vn*; (iv) *i:* an initial shape structure consisting of elements of *vt* and *vn*. Shape grammars not only provide a great plasticity but also allow to keep a visual "identity (aesthetic coesion) in the representation of an abstract morphology (Stiny 1975).

Regarding the computational generation of these rules, we did look at the problem from a physics point of view. We applied a physics approach to modulate the line motion and therefore obtain a visual expression resulting from this. For this reason, we restrain the graphic representation of associations to the vectorial domain. As a clarification, our main interest is not to test an isolated visual feature but instead a combination of features or visual aspects.

Our main contribution consists in providing a solution to a non-verbal visual communication for multi-domain contexts, which in turn can be used to motivate/inspire creative applications among others.

Related Work

Abstract forms of non-verbal communication have been widely explored by expressionist painters like Wassily Kandinsky (Kandinsky and Rebay 1979) and Paul Klee (Klee and Moholy-Nagy 1953). Along with their visual interpretations, they shared the belief that certain combinations of color, light and form would enhance the visual experience.

Aiming to find an empirical way of bridging artistic domains (like music or visual expression) and human perception several models of emotion have been proposed (Russell 1980; Hevner 1936; Brattico and Pearce 2013). The most popular models are the dimensional and discrete models of emotions. Dimensional models have attempted to identify a series of dimensions capable of representing all possible emotional states (Brattico and Pearce 2013; Buechel and Hahn 2017). To overcome the limitations of dimensional models, several authors have proposed discrete models of emotion that use other categories to classify emotion and some additional categories as well (Brattico and Pearce 2013; Buechel and Hahn 2017; Scherer 2000).

Most studies found in literature relating emotions and visual aspects have limited their experiments to the visual features of color (hue, brightness, saturation) and shape. In general, brighter colors have been associated with positive emotions whereas darker colors have been associated to negative emotions (Marks 1996; Barbiere, Vidal, and Zellner 2007). Regarding form, round shapes have been mostly associated to positive emotions like calm and pleasure whereas sharp shapes have been linked to negative emotions like fear and anger (Cavanaugh, MacInnis, and Weiss 2016; Ramachandran and Hubbard 2001). Particularly, Cavanaugh, MacInnis, and Weiss have conducted an interesting study on the use of multiple perceptual dimensions to differentiate emotions.

On the computational application of these cross-modal associations, examples of perceptually based tools relating auditory and visual dimensions can be found in the works of Grill and Flexer and Lindborg and Friberg. While Grill and Flexer (2012) relied on an exploratory visualization to produce sound with perceptually relevant textural metaphors, Lindborg and Friberg (2015) investigated associations that may arise at emotional levels on modal correspondences between certain sounds and colour.

Vocabulary and Grammar Rules

In this section we present a set of visual features and rules to manipulate and transform their expression. The definition of the vocabulary and grammar rules are key aspects, as we propose a grammar based approach for the computational generation of the image-emotion associations.

The Dataset

A Literature research on emotions and visual features was conducted (Scheerer and Lyons 1957; Karwoski, Odbert, and Osgood 1942; Cavanaugh, MacInnis, and Weiss 2016; Lyman 1979; Poffenberger and Barrows 1924; Collier 1996; Lindborg and Friberg 2015; Peters and Merrifield 1958) to collect a dataset of relevant features and therefore build an alphabet of abstract visual symbols.

Inspired by the visual grammar proposed by Leborg, we gathered a set of visual features that can be organized into distinct sections. These include features such as shape, color, size, texture, stroke, contours, density, visual complexity, visual distribution, balance, and geometric transformations. However, as we previously said we restrained this study to a vectorial expression of line and so we do not explore features such as texture, other shapes, closure, high-level features, the geometric transformations of scale and reflect.

Graphic Representations

The movement of line was determined by (i) time (duration and repetition of events) and (ii) a set of visual features. Time determined whether the current visual configuration was repeated or not. A visual demonstration of these can be found in figure 1.

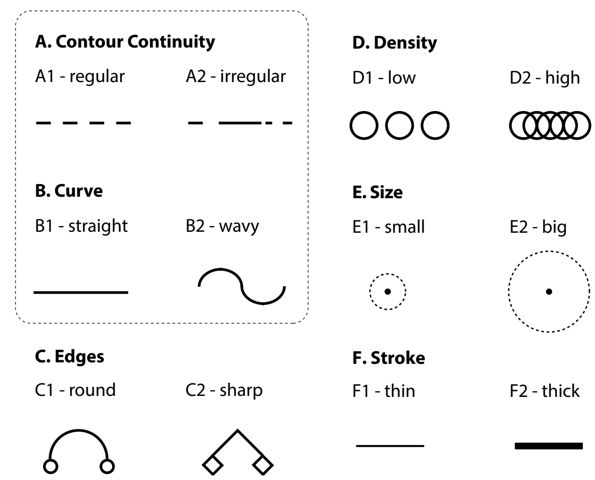

Figure 1: Visual morphology.

A *"regular"* classification means that the current visual motif repeats itself in regular periods of time and *"irregular"* means that the current visual motif will change over irregular periods of time. The visual features approach the following aspects: continuity, curve, edge, density, size, and stroke. The reason for introducing the aspect of time and motion in image is that in the future work we pretend to integrate musical aspects as well.

"Straight" classification was interpreted as a constant, i.e., no variations in angular velocity except in the case of irregular continuity. *"Wavy"* was interpreted as line movement with variations in angular velocity. They could range from soft changes - if we want to achieve a "round" path - to abrupt changes - if we want to achieve a "sharp" path.

"Density" was interpreted as the distance between the current location of the line and the next location, i.e., a smaller distance will produce a higher density and vice versa.

"Size" was visually interpreted as the diameter surrounding the current location of line when compared to the baseline. In future experiments size may be interpreted as the length of the line as well.

"Stroke" was represented as the thickness of line.

A Dynamic Computational Interpretation

We propose a visual interpretation inspired by the laws of physics on motion (linear velocity, acceleration, and angular velocity). For the purpose of this study linear velocity and acceleration can be held a constant or vary over time. The physical attribute that is most relevant in this case is angular velocity. Table 1 gives an overview on the type of changes that are made in order to produce the desired visual motion.

Table 1: Translation of physical dimensions to a *line motion*.

Morphology		**Lin Vel & Acc**	**Angular Velocity**
contour	*regular*		constant
	irregular		irregular change
curve	*straight*	constant	constant
	wavy	or variable	soft or abrupt change
edges	*round*		soft change
	sharp		abrupt change

The Generative Effect Although we follow a set of grammar rules our system has a generative side. This happens because the variables of each visual parameter (size, density, curve, edge, and stroke) are chosen from a random of values within a specific range. For example, for big size, the size output may be a float that can range from “3” to “6”. That is, we defined minimum and maximum values for each category (e.g. small, medium, big) of a visual feature.

The Experiment

To validate the previously established associations and combinations of visual features for the line motion, we conceived an experiment. In this section we explain the methodology used in the conception of our experiment.

User Study

The user study consisted of two parts. The first, where an image was presented - that we believed to be the most representative of a certain emotion - we asked participants to identify the emotion presented in it. The second, consisted of observing four possible visual expressions animated to represent a specific emotion and choosing the most representative image regarding an emotion at a time. In both cases, participants had the possibility to choose the option of ”none of the above” in case they considered that none of the options was good enough.

Visual Setup

The choice for the images to be presented was based on literature findings but also on personal choices. The reasons for the latter, of adding features characteristics that were not presented in literature, was that we wanted to test as many possibilities as we could and had to adjust others to our visual interpretation data in order to promote expressive outputs. The visual configurations used in the first part of the experiment can be consulted as well in table 2.

Visual features that weren’t mentioned in literature but were also considered were inspired by non empirical works of Visual Artists like Oskar Fischinger and Abstract Painters.

Results

This experiment gathered the opinion of a total of 45 participants. The average age was 31.8 with a standard deviation of 10.3. Out of the 45 participants, 51.1% were female and 48.9% were male. Additionally, we questioned whether they had a background in visual communication or not, to which 33.3% answered ”yes” and 66.7% answered ”no”. In this section we presented the results obtained both in Part 1 and 2 of the experiment.

Table 2: Experiment setup: Part 1.

E	**Cont.**	**Curve**	**Edge**	**Den.**	**Size**	**Stroke**
anger	irreg.	wavy	sharp	high	big	med.
calm	reg.	wavy	round	low	med.	thick
happy	irreg.	wavy	round	med.	big	thin
sad	irreg.	wavy	round	low	small	thick

Part 1

In “Part 1” of the study we aimed to evaluate whether the participant’s choice of emotion did correspond to a specific animated expression of the line (through a pre-defined setup of visual configurations (see table 2) or not.

The visual configurations that succeeded the most, regarded the visual representation of the following emotions: “calm” (77.8%), “anger” (71.1%), and “happy” (68.9%) respectively. Surprisingly, the same combination of features in the representation of “anger” in the second part of the test was chosen by a slightly smaller number of participants (46.7%). “Sad” (35.6%) was the emotion where participants had the biggest difficulty to associate with the presented animation. This is congruent with results obtained in the second part of the experiment where this same representation of sadness was chosen by 26.7% of participants (see table 3 and table 4).

Additionally, associations were made to other emotions than the expected. For instance, “Anger” and “Calm” visual representations were associated with “happy” and “sad” emotions. “Happy” visual representation was associated to “calm” and “sad” emotions. “Sad” was associated to “calm” and “anger” emotions. In spite of this, we should note that these associations to other emotions than the desired ones were made by a small amount of participants (no more than 17.8%, see table 3).

Overall, all the other emotion classification by participants matched the desired representations, except in the case of sadness (see table 3).

Table 3: Experiment results: Part 1.

Emotion	**Expected**	**None**	**Other**
anger	71.1%	22.2%	6.7%
calm	77.8%	4.4%	17.8%
happy	68.9%	13.3%	17.8%
sad	35.6%	57.8%	6.6%

Part 2

Looking at table 4 at the results of part 2 of the experiment we can see the most preferred visual configurations for emotions by participants.

"Anger" stands out from the remaining emotions because it had two expressions with divided opinions among participants (46.7% and 40%). The difference between them lies on the features of density, size and in this particular case of visual interpretation of "wavy" and "sharp" line. While on the first case a circular motion with sharp edges was applied (see in table 4 anger a), on the second case (see in table 4 anger b) it was generated a wavy motion with sudden changes of direction and therefore sharp edges.

"Calm" and "Happy" chosen visual configurations (62.2% and 75.6% respectively) were congruent with the visual setup of part 1, meaning that it is has been found a satisfactory combination of visual features.

As for the "Sad" emotion visual configuration, even though it was chosen approximately by half the population (48.9%) which isn't a choice by great majority. When we compare this to the results of others and consider the results of Part 1 of the study as well, it leads us to think that we found a better visual representation for this emotion.

Table 4: Experiment results: Part 2.

E	p%	Cont.	Curve	Edge	Den.	Size	Strk.
anger	a:46.7	irreg.	wavy	sharp	high	big	med.
	b:40	irreg.	wavy	sharp	med.	med.	med.
calm	62.2	reg.	wavy	round	low	med.	thick
happy	75.6	irreg.	wavy	round	med.	big	med.
sad	48.9	reg.	straight	—	—	—	thick

General Findings

Overall, the same combinations for visual features to represent emotions oscillated a bit between part 1 and part 2 of the study. When compared to first part, in the second part there was a tendency to decrease the choice over the same visual configurations presented in part 1. The only exception to this was with the emotion "Happy", because participants enhanced this option by increasing their choice in 6.7% comparatively to part 1. Despite these oscillations, calm seemed to be the emotion with the visual representation more accepted among all the participants. As for the visual representations of "anger" and "sad" (see 2) users preferred with a slightly different visual configurations. The visual representation of "sad" was the one that least matched the previously established findings.

By comparing the results obtained in experiments with previously established associated in literature (Scheerer and Lyons 1957; Karwoski, Odbert, and Osgood 1942; Cavanaugh, MacInnis, and Weiss 2016; Lyman 1979; Poffenberger and Barrows 1924; Collier 1996; Lindborg and Friberg 2015; Peters and Merrifield 1958), we confirm the following findings between visual features and emotions: (i) "anger" associates to wavy, sharp, high density, big size and medium stroke; (ii) "calm" associates to regular contour, round edge, thick stroke; (iii) "happy" associates to round edge, big size, and thin stroke; (iv) "sad" associates to regular contour and thick stroke. Visual features that weren't mentioned in literature but were also considered relevant in the experiments done in our study concerned the following features: irregular continuity in the case of "anger"; wavy curve , low density and medium size in the case of "calm"; irregular contour, wavy curve, and medium density in the case of "happy"; straight curve and low density in the case of "sad".

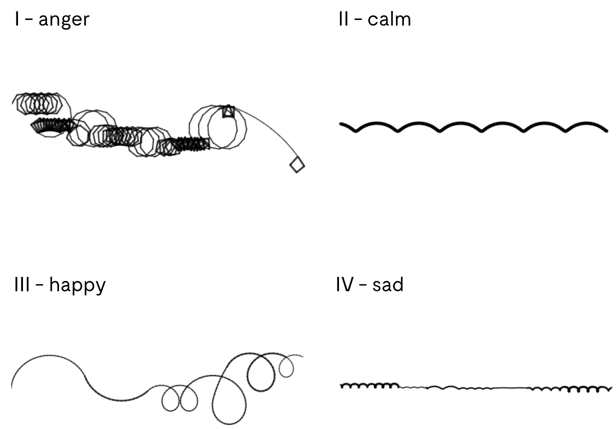

Figure 2: Visual configurations presented in the first part of the experiment. As these images are animated gifs, we made them available in the following url: https://bit.ly/2GQoB8p

Further Explorations

In future work we aim to explore more visual features and apply an Evolutionary User Guided Algorithm to evolve and explore new combinations of visual features. This evolutionary approach has two benefits: the generation of associations that suit the preferences of the user (% of being chosen that a visual feature has regarding a specific emotion); and the analysis of the interactions of the use that may allow a better understanding on the users perceptual motivations.

Other aspects of concern relate to the measurement of some visual elements that are not trivial, as it is the case of the complexity of an image for instance. Another aspect that may be relevant in the future is related to the degree of intensity of an emotion (e.g., joy vs happy or sad vs devastated), i.e., how different degrees of intensity are represented visually.

Conclusion

We have presented a system that is capable of generating dynamically associations between a set of visual features (translated into a line expression) and emotions. We did user tests to validate and tested these multi-modal associations. Results of the system output were satisfactory in the sense that they confirmed the perceptually established associations between line features and emotions. Moreover, we suggested new associations between emotions and visual features that weren't suggested on experiments from other authors. Afterwards, we discussed some challenges faced in the development and exploration of such an interdisciplinary work as well as improvements to be done in future work such as the introduction of an evolutionary user guided algorithm.

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