Textual Affect Communication and Evocation Using Abstract Generative Visuals

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***Abstract*—In order to facilitate interaction in computer-mediated communication and enrich user experience in general, we introduce a novel textual emotion visualization approach, grounded in generative art and evocative visuals. The approach is centered on the idea that affective computer systems should be able to relate to, communicate, and evoke human emotions. It maps emotions identified in the text to evocative abstract animation. We examined two visualizations based on our approach and two common textual emotion visualization techniques, chat emoticons and avatars, along three dimensions: emotion communication, emotion evocation, and overall user enjoyment. Our study, organized as repeated measures within-subject experiment, demonstrated that in terms of emotion communication, our visualizations are comparable with emoticons and avatars. However, our main visualization based on abstract color, motion, and shape proved to be the best in evoking emotions. In addition, in terms of the overall user enjoyment, it gave results comparable with emoticons, but better than avatars.**

***Index Terms*—Communications applications, computer applications in social and behavioral sciences, computer applications in arts and humanities, computer graphics applications, multimedia, natural language processing, user interfaces.**

I. Introduction

As the computer technology is commonly used for human communication and expression, there is a vital need for this technology to be more humanized. Toward this goal, Picard [19] introduced the area of affective computing. She defined it as computing that "relates to, arises from, or deliberately influences emotions." Therefore, for a computer system to be truly affective, it should not only be able to recognize and communicate emotions, but also to evoke emotions in humans.

We present an approach to emotion communication and evocation that draws inspiration from the artistic culture of visualization, as opposed to the pragmatic and analytic one (see, e.g., [5], [18], [20], [23], and [44]). Artistic visualization in general fosters metaphor, personal reflection, and evocative aesthetics instead of precision and information communication. Although the artistic aspect of visualization might make it less concrete and cognitively less effective [18], in this paper, we argue that visualization needs to be somewhat artistic and interpretative in order to evoke affects in humans.

Our approach is focused on short textual messages such as real-time instant messages (chat), comments on social media, and microposts (e.g., tweets). By leveraging the power of abstract animations, we aim to enhance and enrich user experience in online communication and interaction dominated by short messages. Our contribution is twofold.

First, we propose an evocative visualization design based on generative abstract animation. To our knowledge, artistic visualization has not been used in such a context so far. We argue and confirm in our study that such visuals can improve computer-mediated human communication.

Our second contribution is an empirical study that compares several visualization types in terms of emotion communication and evocation features, as well as the overall user experience. We compared our two abstract visualizations with other common emotion visualization techniques (specifically, animated chat emoticons and avatars), in the context of a visual chat system.

This paper is organized as follows. Section II presents related work. Section III describes our research framework. Section IV is devoted to our visualization approach. Section V includes the experimental methods, and Section VI contains the results. The discussion is in Section VII, and the conclusion in Section VIII.

II. Related Work

Kosara [20] defines a continuum between pragmatic visualization, which is utilitarian in nature, and artistic visualization, whose nature is sublime ("that which inspires awe, grandeur, and evokes a deep emotional and/or intellectual response"). Gaviria [12] proposes an explicit definition: "functional information visualizations aim to convey a message or delineate patterns hidden in the represented data through metaphors that users can quickly understand, while aesthetic information visualizations are more concerned with presenting a subjective impression of a dataset by eliciting a visceral or emotive response from the user." Lau and Moere [5] define a model of information aesthetics with two actors: mapping techniques and data focus. Mapping techniques vary from direct to interpretative; data focus varies from intrinsic to extrinsic (evocative). In this respect, interpretative and extrinsic visualizations match Kosara's sublime: Their goal is not just to communicate information, but to invoke personal reflection.

These two interwoven, but distinct cultures in the field of visualization (the pragmatic one, with scientific, technical, and analytical orientation; and the culture oriented to aesthetics, metaphor, and artistic value) are discussed.

A. Pragmatic Visualization of Emotion-Related Data

In [29], a colored bar is introduced as a tool for text visualization and navigation. The sequence of emotion-related colors corresponds to the progression of affect through the document. Another system, i.e., VIBES [13], employs several visualization modes in the form of simple graphs and word clouds in order to depict important emotion-related content of Weblogs. Similarly, Gregory *et al.* [41] suggest using various graphs and pie charts for affective analysis of large textual corpora. Quan and Ren [8] also propose a color-coded timeline for blog emotional content. However, as our context is not analytics but communication and evocation, we will focus more on the artistic visualization.

B. Emotion-Related Visualization Art

Manovich [39] proposes two main characteristics of artistic visualization: 1) It is done in order to transform the complexity of data into visual representations aimed at amplifying human cognition; and 2) it is not about mapping abstract data into something meaningful and beautiful, but about how to represent subjective personal experience of interaction with data. Viégas and Wattenberg [23] describe four key characteristics of artistic data visualization: 1) It must be grounded in real data rather than the mere visual appearance; it requires mapping between data and image; 2) it must focus on aesthetics based on artistic intent; 3) its purpose is to express the artist's point of view and to change the way people think; and 4) artistic visualization is work done with the intention of making art. Nevertheless, some authors (e.g., Sack [18] and Manovich [39]) view evocative and artistic qualities of a visualization as being opposed to the requirements of human–computer interaction (HCI) design. According to those authors, clarity and cognitive efficiency are crucial for HCI. Finally, Whitelaw [44] poses a question: "Does data art become simply an aestheticized (and perhaps functionally impaired) form of scientific data visualization?" He states that by pulling the user away from preconceived, well-formed information, data art offers potential for new and personal reconstruction of information.

Papers such as [3], [15], [23], and [25] debate the power of visualization not only as a tool for visual analytics, but as an artistic and rhetorical medium as well. In addition, some researchers (e.g., [5], [7], [20], [25], [38], and [43]) stress the power of abstract animation and visualization to convey and provoke emotions in users. Artistic visualization does not present information in a literal sense, in terms of HCI usability. Artistic mappings tend to be subjective, to require user imagination, and to emphasize experience over data.

For example, there are systems that attempt to depict emotions taken from online texts, reflecting not on personal writing but on the collective aspect of feelings on the Web. One project, "We Feel Fine" by Harris and Kamvar [33], collects blog entries that mention the word "feel." Users are invited to search its database through a series of artistic interfaces. Similarly, the Dumpster project [24] searches and visualizes textual occurrences of romantic breakups.

Some put emotion visualization in the context of generative art. For example, the Aesthetiscope [26], given a textual input, generates an artistic visual output in the form of colored squares. The authors define their endeavor as visualizing the aesthetics of reading, stressing that the reading process does not only involve logic, but emotion and sensation as well. Furthermore, the Painting Fool, i.e., a generative portrait painting system [6], uses image recognition methods to analyze facially expressed emotions of a viewer filmed by a camera. The system then paints the viewer's artistic portrait. Each emotion carries a distinctive visual style. Some visualize the sentiment of human dance movements via abstract animation (e.g., [25] and [30]) or use image synthesis to arouse viewers [52].

In terms of color palettes, Liu and Maes [26] extend the Munsell's color space [4] and use prescriptive color psychology theories of Berlin and Kay [14] and Goethe [36]. The authors manually annotated their affective lexicon with the descriptive vocabulary of color parameters. Furthermore, in [6], the authors developed emotion-to-color mappings for the Painting Fool by using their own subjective impressions. They used grayish colors for the emotion of disgust, blues and grays for fear, and very vivid colors for happiness. Dance-to-color mappings by Subyen *et al.* [25] are defined by synesthetic color rules proposed by Kandinsky [11]. However, none of these color approaches are truly based on an empirical study.

C. Emoticons and Emotional Avatars

One may claim that the simplest form of computer-mediated affect expression is an emoticon, a typographical representation of a facial expression. Potentially, emoticons communicate human emotions more explicitly than words [49] and are a widely used resource in the field of affective computing and sentiment analysis (e.g., [27], [50], and [51]).

In contrast with emoticons that are selected manually, a popular approach in affective computing is presenting emotions via artificial and automatic anthropomorphic avatars. We argue that the avatar subculture is somewhere in between pragmatic and artistic cultures in visualization (with distinct features of its own). Artificial characters range from users' expressive photographs [1] and very simple avatar drawings [28], to computer animated avatars: 2-D cartoon characters (e.g., [9], [17], and [31]) and realistic 3-D human head models (e.g., [21], [32], [34], and [40]). Persson [31] shows how interplay between pure text and animation significantly improves the expressiveness of messages. Olveres *et al.* [32] demonstrate that the majority of the users enjoyed using an animated interface with an intelligent emotional avatar head more than a static nonanimated interface or a text-only interface. Fabri *et al.* [40] show that subjects were more involved when using emotional than nonemotional avatars. Neviarouskaya *et al.* [9] show that a quality of user experience of an avatar system based on automatically selected emotions is on the level of an analogues system with manually selected emotions. However, the study showed that emotional avatar systems are not by any criteria better than nonemotional avatars. As far as we know, no study has compared the evocative value of emotional avatars with other forms of visualizing emotions, such as abstract animation.

Despite popularity of avatars and emoticons, we hypothesize that generative art and artistic visualization offer a better solution for invoking feelings in people. For a visualization system to be affective in terms of being able to evoke real affects, it has to be sublime [20]. Since emotions are, communication-wise, inherently ambiguous, imprecise, and culture-dependent, our premise is that they should be depicted in a more subtle, metaphorical, and interpretative way.

III. Research Framework

Our visualization approach aims at facilitating: 1) *emotion communication*, the ability of the visualizations to convey and represent emotions to users; 2) *emotion evocation*, the ability to elicit, affect, and stimulate emotions in users; and 3) *overall user enjoyment:* responsiveness of the system, distractive features, aesthetic qualities, general satisfaction, and readiness to use visualization in real life chat.

We grounded our approach in six basic emotional categories defined by Ekman [16]: happiness, sadness, anger, fear, disgust, and surprise. Krcadinac *et al.* [27] present a comparison of different models of emotions, which shows the prevalence of Ekman's model.[1] However, we acknowledge the widespread use of dimensional models for assessing emotions versus discrete ones (such as Ekman's). As stated by Mauss and Robinson [2], both models have their pros and cons; there is no "gold standard" in measuring emotional responses.

To represent emotional type and intensity via abstract visual animation, we designed and developed two visualization systems. The first one is primarily focused on color and is implemented in a visualization system called Hooloovoo. The second and main one combines color, motion, and shape, and its implementation is called Synemania. To examine whether and to what extent these two visualization systems (presented in detail in the following section) lead to the realization of the above stated objectives, we defined the following research questions:

RQ1: Whether and to what extent users are capable of differentiating the type of emotion communicated by our main visualization,[2] Synemania? In other words, is Synemania able to communicate emotional types it is supposed to convey? In addition, do Synemania visualizations differ in their ability to communicate emotional type?

RQ2: Whether and to what extent our visualizations, Hooloovoo and Synemania, and two common emotion visualization techniques—emotional avatars and animated chat emoticons—differ from one another in terms of *perceived emotion communication?* We decided to use animated emoticons and emotional avatars because they are standard forms of visualizing textual emotions on the Web (see Section II-C); as such, they could be viewed as a form of a baseline.

RQ3: Whether and to what extent Hooloovoo, Synemania, emotional avatars, and chat emoticons differ in terms of *perceived emotion evocation?*

[1] http://www.krcadinac.com/synesketch/research/tac_syn_appendix.pdf

[2] We did not test Hooloovoo in the same way because Hooloovoo's design is restricted to simple color grids whose associations with emotions have already been examined in previous emotion and color research [37].

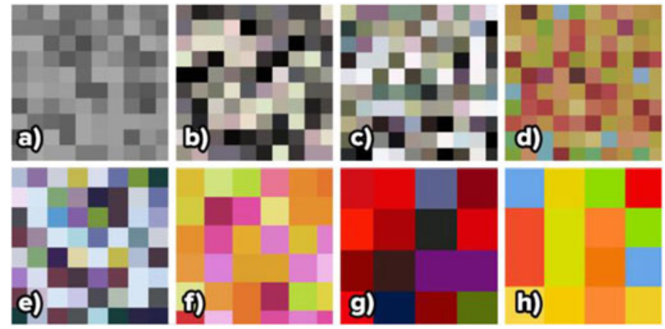

Fig. 1. Hooloovoo visualization. (a) No emotion recognized. (b) Weak disgust. (c) Weak fear. (d) Weak happiness. (e) Sadness. (f) Surprise. (g) Strong anger. (h) Strong happiness.

RQ4: Whether and to what extent Hooloovoo, Synemania, emotional avatars, and chat emoticons differ in terms of the *overall user experience?*

IV. Visualization Design

A. Hooloovoo: Focus on Color

In order to examine our approach to color, we designed Hooloovoo, a simple animated grid of colored squares.

Mapping emotion to color is faced with problems of subjectivity and dependence on a particular culture. For an objective ground for our color palettes, we relied on the emotion-color mappings given in [37], which investigated how people from different age and cultural groups associate colors with Ekman's emotional types. Participants were asked to choose color samples and associate them with the facial expression for each emotional type. They associated light colors with the emotions of happiness, surprise, and fear, while sadness, disgust, and anger tend to be associated with darker colors. Colors related to sadness and fear are very desaturated; happiness, surprise and anger are, on the contrary, highly chromatic.

For Hooloovoo, we used color palettes from [37], adjusted by findings in [22]. For example, Valdez and Mehrabian [22] state that high brightness and saturation tend to be connected with pleasure and arousal. We decided to increase the brightness of the color palette for positive emotions (happiness) and the emotion of surprise and decrease it for negative emotions (sadness, anger, fear, and disgust). Hooloovoo's saturation, square sizes, and frame rate change according to the type and intensity of the most intense emotion recognized in the text. Stronger emotions are depicted by larger squares, higher saturation, and faster frame rates. Examples of Hooloovoo's visuals are shown in Fig. 1.

B. Synemania: Combining Motion, Shape, and Color

Our second visualization, called Synemania, uses both color and abstract animation to evoke emotions. Synemania is a drawing system of colliding particles. Its generative algorithm is based upon the Bubble Chamber [35], which is itself an artistic adaptation of graphs made by accelerator experiments in particle

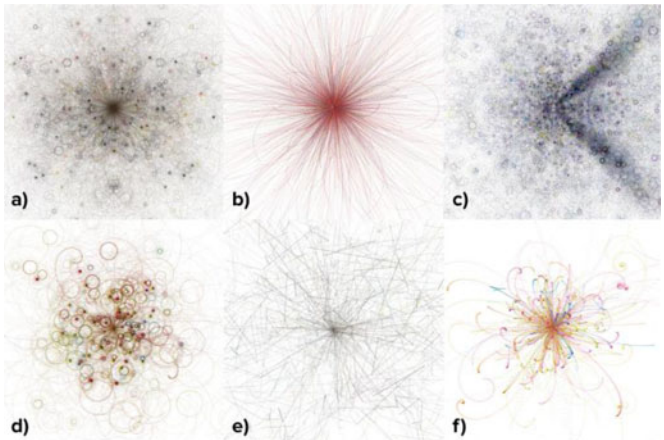

Fig. 2. Examples of Synemania visuals representing six emotional types. (a) Disgust. (b) Anger. (c) Sadness. (d) Happiness. (e) Fear. (f) Surprise.

TABLE I
SYNEMANIA MAPPING OF EMOTIONAL TYPES TO MOTION AND SHAPE

Emotional Type	Motion and shape
Anger	Fast, intense and dense radial lines
Happiness	Curvy lines which form calm round shapes
Surprise	Fast, dense, and curvy lines; random directions
Fear	Jerky, angular lines moving in random directions
Disgust	Calm dot pattern, slowly appearing; particles gravitate toward black spots
Sadness	Calm dot pattern, slowly appearing, tremulous, slightly shimmering

physics. Each new emotion recognized in text (e.g., during a chat session) starts a new explosion of colliding particles. Each emotional type has its own type of particles and its own generative discrete differential equation. By moving, particles draw paths, which form various visual patterns. These patterns are intended to represent the type and intensity of emotions. Stronger emotions are being presented with a higher saturation and a higher number of particles. The emotion-image mapping is illustrated in Fig. 2.

We found an empirical foundation for motion and shape of our visualization in design principles defined in [38], [42], and [43]. Straight motion paths are perceived as positive and calm, while jerky, angular motions as negative and threatening; radial out motion can be perceived as neutral. In addition, the speed of animation increases the intensity of emotion, e.g., excessive speed can be perceived as threatening. We also grounded motion attributes in our own subjective criteria; after all, artistic and sublime qualities of a visualization imply personal experience [39], personal point of view [23], and enigmatic and irrational [20]. Our emotion-to-motion mapping appears in Table I. A demonstration video of Hooloovoo and Synemania is available online.[3]

[3] www.youtube.com/watch?v=u5kznE6kYmc

V. METHODS

A. Participants

Fifty-seven participants took part in our study (31 females and 26 males). All regularly use computer-based communication software (such as chat) and speak/read/write English fluently. Thirty-nine of them (68.4%) did not have experience with any emotion visualization software before this study. Thirty-five subjects (61.4%) were 30 or younger.

B. Procedure

The study included two parts. In the first part, each participant was presented with seven Synemania animations (associated with images) in a random order. These animations included six emotional types from Fig. 2, plus the neutral emotional type. After watching all the animations, the participants were asked to associate each of the emotional types with the animation that matched the given type the best.

In the second part of the study, each participant was presented with four videos, one for each visualization type (Emoticons, Avatars, Hooloovoo, and Synemania), in a random order. After watching each video, the participants were asked to fill in the questionnaire presented in Table III. The participants were requested to take a 10-min break between the second and the third video.

The subjects were also asked to rank the four visualization types according to their own overall enjoyment and impression, from the best to the worst (1 best; 4 worst).

All of the participants signed a consent to participate in the study. They were told about the general objective of the study (comparing different visual interfaces in terms of textual emotion visualization). However, none of the participants were explained the study's research questions or hypotheses; therefore, their prior knowledge about the study could not have interfered with their opinions or answers.

C. Materials

In order to support the first part of the study, we prepared seven Synemania animations in the form of generative programs, one for each emotional type and one emotionally neutral. Generative programs were designed as executable Java files; their only output was the animation. Animations were associated with a characteristic image, a frame of the animation (like those shown in Fig. 2). Fig. 3 presents screenshots of generative animations for the emotions of surprise, disgust, and anger. Note that participants were shown both animations (see Fig. 3) and static pictures (see Fig. 2).

The second part of the study was supported with four videos, one for each visualization type: Emoticons (3 min and 18 s),[4] Avatars (3 min and 29 s),[5] Hooloovoo (3 min and 29 s),[6] and Synemania (3 min and 53 s).[7]

[4] https://vimeo.com/39344340
[5] https://vimeo.com/39359649
[6] https://vimeo.com/39360341
[7] https://vimeo.com/39352246

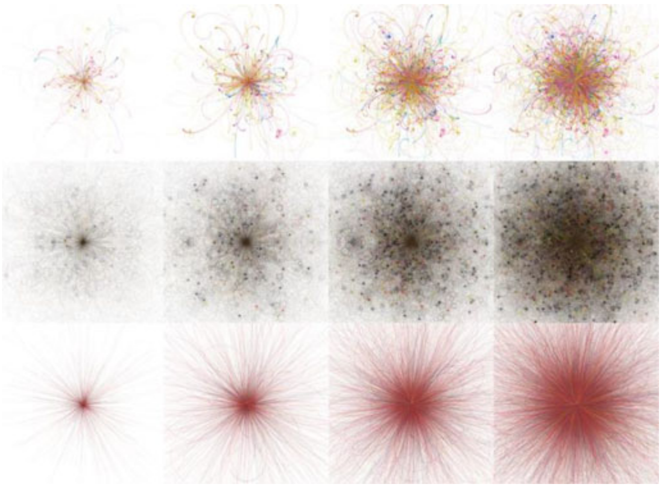

Fig. 3. Examples of Synemania visuals representing the animation development for three emotional types: surprise (top row); disgust (middle row); and anger (bottom row).

Note that Avatars, Hooloovoo, and Synemania visualizations were made using emotional vectors generated by an emotion recognition engine [27], whereas the Emoticons visualization was made by screen capture of a chat conversation with emoticons manually selected to reflect the emotion of conversation.

For Emoticons, we employed standard animated emoticons used by the Skype Instant Messaging software. In the case of Avatars, we used animated 2-D characters whose facial expressions accurately represent Ekman's faces [45]. Design of avatars was taken from the Grimace Project,[8] an application that displays Ekman's emotions through facial expressions of a comic-like face (similar to avatars presented in [9]). Each emotion can be represented on a 0–1 scale; this perfectly fits our visual approach as the same scale is used by the employed emotion recognition engine [27].

Each video presented three chat conversations visualized with one of the examined visualization modes. The first chat was a conversation between two friends, in which the mood changes from loneliness to joy. The second chat was a discussion about a film among multiple people. In the third one, a couple debates their experience in a restaurant. The entire content of the three chat conversations is shown in Table II.

All six emotional types are present in the conversations. In addition, we made sure that all emotions were accurately recognized by the emotion recognition engine. Fig. 4 presents video screenshots of chat conversations for each visualization type.

Each video was followed by a same questionnaire with 11 question statements. The questionnaire was based on a seven-item Likert-like scale, from *Strongly agree* to *Strongly disagree*. All the questions are presented in Table III, grouped according to the evaluation criteria they belong to.

D. Variables

Independent variable is the visualization type with four levels: Avatars, Hooloovoo, Synemania, and Emoticons.

[8]http://grimace-project.net

TABLE II
CHAT CONVERSATIONS USED IN THE STUDY

Chat 1: Loneliness and Cheering up	
marco:	*eva, i feel lonely today . . .*
	so lonely
	very, very lonely!!!!!!!
eva:	*listen, marco, dont be so tearful!*
	i do not allow you to be lovesick!
marco:	*i know, i'm mad at myself too . . .*
	but, it's like i'm full of something verminous
eva:	*listen, i know what's going to cheer you up—i just bought two tickets for the bob dylan concert in belgrade :D*
marco:	*WOW thanks eva!*
eva:	*:)*
Chat 2: About a Film	
hanna:	*the movie was strange . . . i was full of anxiety all the way to the end . . .*
maya:	*yes, but its name will be written in golden letters in the history of cinematography!*
hanna:	*i was furious when i saw that actor! what a jerk.*
lee:	*the movie was just YUCKY*
sergey:	*the director did put THOSE scenes?!??! man, the guy is so brave . . .*
Chat 3: About a Restaurant	
peter:	*the meal in that restaurant was so awful.*
aisha:	*yeah, gross!!!*
peter:	*and i hated the waiter . . .*
aisha:	*i was afraid my stomack will get infected.*
peter:	*good thing we made the dinner ourselves later.*
aisha:	*yeah, and it was awesome!*

We have defined three dependent variables.

1) Emotion Communication, *EmoCom*, is the perceived affect communication ability of a visualization type and is calculated as the average of Q1 and Q2 in Table III.
2) Emotion Evocation, *EmoEvo*, is the perceived affect evocation ability of a visualization type and is calculated as the average of Q3, Q4, and Q5 in Table III.
3) Overall User Enjoyment, *OverUserEnj*, is the perceived quality of a visualization type related to its responsiveness, ambient feel, distractive effect, aesthetics, applicability to real life chat, and satisfaction in general. It is calculated as the average of Q6–Q11 in Table III. For Q7, the scale is inverted because the highest score in Q7 means the highest distraction, which is the lowest quality for a visualization type. The inversion is done by subtracting the user responses from 8 (the questions are based on seven-level Likert-type scale).

E. Experimental Design and Data Analysis

The first part of the study, focused on RQ1, was aimed at assessing the participants' ability to associate Synemania's visuals with appropriate emotion types (six emotion types defined by Ekman plus neutral type). The collected data were analyzed using the Chi-Square test.

The second part of the study, intended to address RQ2–4, was designed as a repeated measures within-subject experiment. The experiment was aimed at assessing how end-users perceive *emotion communication* (RQ2), *emotion evocation* (RQ3), and *overall user enjoyment* (RQ4) qualities of the four examined visualization types: Emoticons, Avatars, Hooloovoo, and

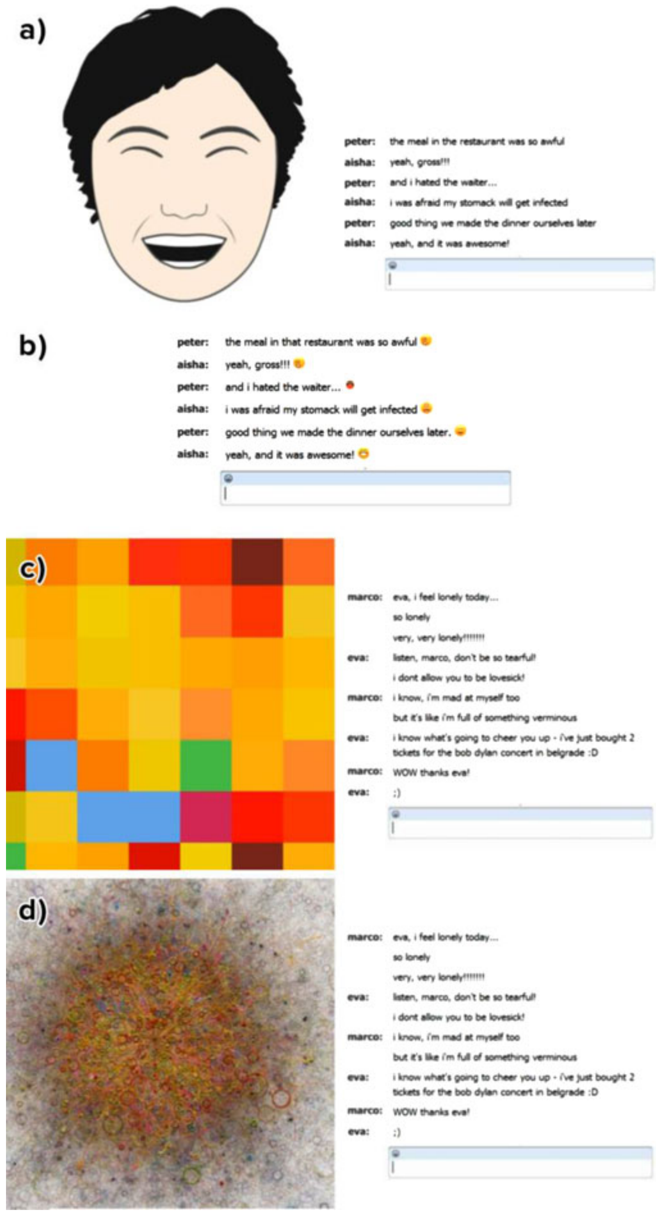

Fig. 4. Video screenshots of chat conversations for each visualization type: (a) third chat conversation visualized by avatars; (b) third chat conversation visualized by emoticons only; (c) first chat conversation visualized by Hooloovoo; (d) the first chat conversation visualized by Synemania.

Synemania. The data collected in this part of the study were analyzed using standard descriptive statistics (mean and standard deviation).

In addition, to analyze the effect of different visualization types on the participants' perception of *emotion communication (EmoCom)*, *emotion evocation (EmoEvo)*, and *overall user enjoyment (OverUserEnj),* one-way repeated measures ANOVA tests were employed, with chosen significance level of 0.001. We verified that the ANOVA assumptions were satisfied. Since variables *EmoCom, EmoEvo,* and *OverUserEnj* were not normally distributed, ANOVA tests were done with log-transformed data. Mauchly's test was performed to determine if the assumption of sphericity had been violated. If so, degrees of freedom were corrected using Huynh–Feldt correction or Greenhouse–Geiser correction depending on whether the value of the Greenhouse–Geiser estimate of sphericity was larger than 0.75 or not [10]. If a significant effect was found, we did post-hoc analyses using paired *t*-tests to compare all pairs of independent variables. Both sequential Bonferroni and the false discovery rate (FDR) correction methods [46] were applied to all pairwise comparisons of independent variables to prevent the rise of Type I error rate (alpha inflation) associated with multiple testing.

As the second part of RQ4 assessment, we calculated the median visualization ranking (1–4) for each emotional type.

All our statistical tests were performed using SPSS Statistics software tool.

TABLE III
QUESTIONNAIRE

Criteria	Questionnaire items	
Emotion Communication	Q1	*The visualization was successful at conveying/communicating/representing the emotions expressed in the text*
	Q2	*I understood the emotions that were visually presented*
Emotion Evocation	Q3	*The visualization was successful at affecting/stimulating/evoking my emotions*
	Q4	*The visualization intensified/amplified the emotions expressed in the text*
	Q5	*If I would be using this visualization for a chat conversation, it would inspire my textual input*
Overall User Enjoyment	Q6	*The visualization gave an appropriate/good ambient feel to my text*
	Q7	*If I would be using this visualization for a chat conversation, I would be distracted by it*
	Q8	*I am satisfied with the experience of using this visualization*
	Q9	*The visualization was aesthetically pleasing*
	Q10	*I would enjoy this visualization in my chat conversations*
	Q11	*If I would be using this visualization for a chat conversation, I would enjoy the chat more*

VI. Results

A. *RQ1: Association Between Emotion Types and Synemania's Visuals*

We present the overall frequencies between all emotional types and all Synemania visualizations (see Table IV). The percentage correct is listed along the diagonal. The average percentage accuracy across the seven types was 60.6%. The neutral visualization was easier to identify as it was desaturated, lighter, and less dense. Excluding the neutral case, the average across the six remaining types was 57.3%.

In response to RQ1, it is fair to conclude the relatively poor ability (in terms of average precision) of Synemania to communicate the exact emotion type it is intended to depict. However, the large share of "wrong" associations appears to be due to similar emotion types, for example, happiness visuals are being mistaken for surprise ones, fear visuals are being confused with sadness and disgust ones, etc.

TABLE IV
FREQUENCIES OF VISUALIZATION-TO-EMOTION MAPPING, FOR EACH EMOTIONAL TYPE AND EACH SYNEMANIA VISUALIZATION

Vis.	H.E.	Sd.E.	A.E.	F.E.	D.E.	Su.E.	N.E.
H.	**30** (52.6%)	3	8	1	2	13	0
Sd.	4	**35** (61.4%)	2	7	4	1	4
A.	4	7	**30** (52.6%)	8	4	3	1
F.	5	6	4	**30** (52.6%)	6	3	3
D	7	3	2	4	**37** (64.9%)	2	2
Su.	5	1	8	5	3	**34** (59.6%)	1
N.	2	2	3	2	1	1	**46** (80.7%)

TABLE V
MEAN AND STANDARD DEVIATION FOR ALL DEPENDENT VARIABLES AND FOUR VISUALIZATION TYPES

Variable	Avatars	Emoticons	Hooloovoo	Synemania	p-value
EmoCom	5.33 (1.24)	5.36 (1.2)	3.64 (1.27)	5.7 (1.03)	$< 0.001*$
EmoEvo	3.8 (1.71)	4.05 (1.61)	4.25 (1.42)	5.96 (1.2)	$< 0.001*$
OverUserEnj	3.42 (1.2)	4.94 (0.9)	3.87 (1.44)	5.1 (1.11)	$< 0.001*$

A Chi-Square test identified a significant association between emotion type and visualization, $\chi^2(6) = 16.96, p < 0.01$. However, when we excluded the Neutral visualization from the analysis, the Chi-Square test failed to indicate a significant association.

B. RQ2: Emotion Communication

Emotion communication, which was the focus of our second research question (RQ2), was measured using the variable *EmoCom*. Descriptive statistics for this variable are given in Table V.

The ANOVA results for *EmoCom* indicate significant differences among the visualizations ($F(2.19, 122.63) = 35.95$, $p < 0.001$). The participants acknowledged Hooloovoo as significantly ($p < 0.001$) less communicative than all other visualizations (see Table VI). No significant differences were found between other three visualization types: Synemania, Avatars, and Hooloovoo.

We can conclude that in terms of perceived emotion communication, Synemania visualization (abstract animation with complex motion graphics that include both shape and color) is as good as emotional avatars or manually selected animated emoticons. However, Hooloovoo (a simple color grid) was perceived as significantly worse than Synemania, Avatars, and Emoticons.

C. RQ3: Emotion Evocation

The focus of our third research question (RQ3) was emotion evocation, measured by the variable *EmoEvo*. Descriptive statistics for *EmoEvo* are given in Table V. The one-way

TABLE VI
SIGNIFICANCE LEVELS FOR EMOTION COMMUNICATION VARIABLE (*EmoCom*) BETWEEN ALL VISUALIZATION TYPES, AND THE CORRESPONDING ADJUSTED ALPHA VALUES

Variable	p-value	α_{adj}–seqB	α_{adj}–FDR
EmoCom: Hooloovoo versus Synemania	$< 0.001^*$	0.008	0.008
EmoCom: Hooloovoo versus Avatars	$< 0.001^*$	0.01	0.017
EmoCom: Hooloovoo versus Emoticons	$< 0.001^*$	0.012	0.025
EmoCom: Avatars versus Synemania	0.093	0.017	0.033
EmoCom: Emoticons versus Synemania	0.119	0.025	0.042
EmoCom: Avatars versus Emoticons	0.820	0.05	0.05

Legend: asterisk (*) indicates the compliance of the significance level (i.e., p-value) with the adjusted alpha level; α_{adj}–seqB—adjusted alpha according to the sequential Bonferroni correction method; α_{adj}–seqB—adjusted alpha according to the false discovery rate correction method. Rows are sorted based on the p-value, as the two correction methods require [45]. This legend is also applied to Tables VII and VIII.

TABLE VII
SIGNIFICANCE LEVELS FOR EMOTION EVOCATION VARIABLE (*EmoEvo*) BETWEEN ALL VISUALIZATION TYPES, AND THE CORRESPONDING ADJUSTED ALPHA VALUES

Variable	p-value	α_{adj}–seqB	α_{adj}–FDR
EmoEvo: Synemania versus Hooloovoo	$< 0.001^*$	0.008	0.008
EmoEvo: Synemania versus Avatars	$< 0.001^*$	0.01	0.017
EmoEvo: Synemania versus Emoticons	$< 0.001^*$	0.012	0.025
EmoEvo: Avatars versus Hooloovoo	0.097	0.017	0.033
EmoEvo: Avatars versus Emoticons	0.209	0.025	0.042
EmoEvo: Emoticons versus Hooloovoo	0.361	0.05	0.05

repeated measures ANOVA test with *EmoEvo* as the dependent variable showed a significant difference among the visualization types with respect to the perceived emotion evocation, $F(2.06, 115.23) = 16.59$, $p < 0.001$. The subsequent post-hoc tests indicated that Synemania was perceived as significantly better ($p < 0.001$) than all the other visualization types in its ability to evoke emotions (see Table VII). No other significant difference between the examined visualization types was detected.

As a response to RQ3, we conclude that Synemania, our evocative approach based on color, motion, and shape outperforms all the other visualizations in terms of evoking emotions in users. In the same terms, Hooloovoo (a simple color grid) proved to be as good as Emoticons and Avatars.

D. RQ4: Overall User Experience

For overall user enjoyment (*OverUserEnj*), descriptive statistics are given in Table V. Results of ANOVA test show that there was a significant effect of visualization mode, $F(2.3, 128.61) = 29.83$, $p < 0.001$. Results of the post-hoc tests (see Table VIII) show that the participants were significantly ($p < 0.001$) less satisfied with Avatars than with Emoticons and Synemania. The same finding applies to Hooloovoo, it was perceived as significantly ($p < 0.001$) less appealing than Synemania and Emoticons. Synemania did not prove to be better than Emoticons.

Regarding the visualization type ranking according to the participants' own overall impression, Synemania is notably better than other three visualization types (median rank being 1).

TABLE VIII
SIGNIFICANCE LEVELS FOR OVERALL USER ENJOYMENT VARIABLE (*OverUserEnj*) BETWEEN ALL VISUALIZATION TYPES, AND THE CORRESPONDING ADJUSTED ALPHA VALUES

Variable	p-value	$\alpha_{\mathrm{adj}-}$seqB	$\alpha_{\mathrm{adj}-}$FDR
OverUserEnj: Synemania versus Hooloovoo	$< 0.001^{*}$	0.008	0.008
OverUserEnj: Emoticons versus Hooloovoo	$< 0.001^{*}$	0.01	0.017
OverUserEnj: Avatars versus Synemania	$< 0.001^{*}$	0.012	0.025
OverUserEnj: Avatars versus Emoticons	$< 0.001^{*}$	0.017	0.033
OverUserEnj: Avatars versus Hooloovoo	0.130	0.025	0.042
OverUserEnj: Emoticons versus Synemania	0.302	0.05	0.05

Avatars are the worst (median rank being 4). Emoticons and Hooloovoo have the same median rank (2).

Based on the above results, we can conclude that with respect to the overall user experience (RQ4), our visualization Synemania (which combines color, motion, and shape) is better than Avatars and our second visualization Hooloovoo. Synemania did not significantly outperform Emoticons, but it did receive a higher rank; we conclude that Synemania is either as good as or better than Emoticons. Avatars, however, proved to be significantly less appealing than both Synemania and Emoticons.

VII. DISCUSSION

Especially interesting for our research is the difference in the results obtained for RQ1 and RQ2. Although the results for RQ1 suggest relatively poor ability of a user to "correctly" identify the appropriate emotional type Synemania is supposed to convey, the results related to the perceived emotion communication (RQ2) show that the participants perceived Synemania visualizations as equally good as Emoticons and Avatars (actually, slightly better, but not on a statistically significant level). One should keep in mind, although, the difference between the two parts of the study: In the first part, the participants were classifying Synemania visualizations only by the emotional type; in the second part, they were asked to assess the overall communicativeness of Synemania—which includes other factors too, such as the intensity of the emotion and the aesthetic power of the visualization and text combined.

However, despite these additional factors, the notable difference between RQ1 and RQ2 results still may suggest that the participants' *subjective* opinion or impression about the quality of emotion communication is quite different from the *objective* accuracy of emotion-to-animation mapping (measured by the degree to which the participants understood the exact emotion the visualization was intended to depict). Consequently, we can conclude that an artistic, subtle, metaphorical, and interpretative visualization does not decrease the quality of perceived emotion communication on a *subjective* level of individual users' impressions.

The results obtained for RQ1 suggest that Synemania might be better in communicating emotional valence (emotion being positive, negative, or neutral) instead of an emotional type. It is because participants tended to confuse similar emotional types (happiness with surprise, or sadness with fear and disgust). Thus, it might be interesting to combine our approach with standard graphs and charts in sentiment analysis (e.g., [51]).

Another interesting finding is that Emoticons received better ratings than Avatars in terms of the overall user enjoyment. It implies that users prefer manually selected animated emoticons to emotional avatars. This is in line with research done by Neviarouskaya *et al.* [9], which shows no evidence that an avatar system based on automatically selected emotions provides better user experience than a comparable system with manually selected emotions.

Emoticons are widely used on the Web, while emotional avatars are still only in the research phase; thus, users find emoticons more familiar, which could be the source of the possible bias. Xie *et al.* [48] argue that generating lifelike avatars remains a challenging task despite decades of research, and name possible research directions toward avatars with better expressive quality. In terms of our research, one should keep in mind that the particular design of avatars might have influenced the results; clearly, there is no standard in avatar design. For instance, we employed 2-D avatar design [45] instead of a 3-D or a video-realistic one, advocated by some researchers (e.g., [21], [32], and [48]). In addition, Weerasinghe *et al.* [47] argue that avatars should not encompass only facial expressions, but demographic features and body movements and attributes as well.

In addition, there might be a cultural bias involved, because avatars are far more used in East than West cultures. Further research is needed in order to better understand implications of particular avatar design.

Nonetheless, Synemania visualization proved to be better than avatars and emoticons in evoking emotions (RQ3), and as good as them in communicating emotions (RQ2). Most importantly, Synemania outperformed avatars in terms of overall user enjoyment (RQ4). In addition, despite the familiarity and widespread use of emoticons, Synemania visualization proved to be either as good as emoticons or better (RQ4). It supports our argument about the usability of evocative visualization and confirms that artistic, interpretative, and extrinsic features of a visualization should not be undermined (e.g., [5], [7], [20], [38], [43], and [52]). It may also show that features focused on user imagination and experience are not in collision with good HCI design (as was argued by, for example, Sack [18] and Manovich [39]). Finally, it suggests that realistic avatars should not be the only or primary research goal in the field of computer-aided visual communication and evocation.

Our findings also stress the importance of a particular visual design. Synemania's rich motion texture (color, motion, and shapes) made it concurrent with emoticons and avatars; Hooloovoo was not at all successful. Authors such as [38] and [53] state that, instead of color, motion factors (speed, direction, and path curvature) are crucial to immersive experience. Omata *et al.* [52] show how different color, speed, motion, and shape can arouse or calm viewers. At this point, however, it is hard to compare these systems empirically, since each one of them employs different emotional, visual, and methodological models. Cultural and subjective bias cannot be fully avoided in visual culture, but these findings do suggest that further research may establish stable and comparable elements of evocative visual language.

VIII. Conclusion

We have presented an approach for evocative artistic visualization positioned within the context of computer-mediated human communication and interaction. The main feature of our visualization method is emotion-to-animation mapping, which employs evocative animation in order to paint the user's emotions expressed in written text. The visual design is based both on empirically proven principles and our own subjective criteria.

In the presented study, we tested if our visualizations communicate the exact emotional types they were supposed to depict. We also examined the perceived emotion communication and emotion evocation, as well as the overall user experience by comparing two of our visualizations and two common emotion visualization techniques: manually selected animated chat emoticons and emotional avatars. The results demonstrate that although participants did not show notable success in recognizing the exact emotional types our visualizations were supposed to depict, they perceived our generative art as enjoyable and effective in communicating emotions (as good as other examined visuals). Most importantly, our main visualization, Synemania, proved to be better (on a statistically significant level, $p < 0.001$) than other visualizations in evoking emotions.

In the future work, we plan to examine how exactly different features of the visualization and animation (shape, texture, motion, speed, tempo, rhythm, etc.) affect human emotional states. Based on these findings, we plan to propose some more generalized elements of visual language that could be used in affective abstract animation. We also plan to integrate our approach with sentiment analysis visualization tools.

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