

# The Effect of Color on Expression of Joy and Sadness in Virtual Humans

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## Abstract

*For centuries artists have been exploring color to express emotions. Following this insight, the paper describes an approach to learn how to use color to influence the perception of emotions in virtual humans. First, a model of lighting and filters inspired on the visual arts is integrated with a virtual human platform to manipulate color. Next, an evolutionary model, based on genetic algorithms, is created to evolve mappings between emotions and lighting and filter parameters. A first study is, then, conducted where subjects evolve mappings for joy and sadness without being aware of the evolutionary model. In a second study, the features which characterize the mappings are analyzed. Results show that virtual human images of joy tend to be brighter, more saturated and have more colors than images of sadness. The paper discusses the relevance of the results for the fields of expression of emotions and virtual humans.*

## 1. Introduction

‘Works of art (...) can be expressive of human qualities: one of the most characteristic and pervasive features of art is that percepts (lines, colors, progressions of musical tones) can be and are suffused with affect.’

This passage by John Hospers [1] emphasizes that it is in the nature of art to express emotions and that this expression can be accomplished through the formal elements of art. According to the author, the reason it is possible to perceive emotions in these elements is that people find analogies to the internal and external manifestations of their bodies when experiencing such emotions. Effectively, artists have been exploring for centuries the idea that it is possible to perceive emotions in line, space, mass, light, color, texture, pattern, sound and motion [2]. This paper takes this insight and explores how the manipulation of properties of one such element - color - can accomplish expression of emotions in virtual humans.

Color has been widely manipulated by artists in the visual arts to convey emotion [2, 3]. Color is the result of interpretation in the brain of the perception of light in

the human eye [4]. Thus, the manipulation of light in the visual arts, called *lighting*, has always been a natural way of achieving specific effects with color [5, 6]. In the work presented in this paper, color is manipulated using a lighting model. Moreover, color can also be looked at as an abstract property of a scene and manipulated explicitly with no particular concern for the physics of light. This has been explored in abstract painting [2] and, more recently, in the visual media [7]. The work presented in this paper also explores this form of manipulation and uses *filters* to achieve such color effects. Filters do post-processing of pixels in a rendered image according to user-defined programs [8].

Having defined the means by which color is to be manipulated, the following questions ensue: Can emotions be expressed using lighting and filters? How should emotions be mapped into these forms of expression? The emotions perceived in color are influenced by biological, individual and cultural factors [3]. It is, therefore, a hard challenge to find a mapping between emotions and color properties which is general. Looking at the literature on lighting, it is possible to find general principles on how to convey moods or atmosphere [5, 6, 9, 10] but, these aren't sufficient to differentiate between emotions and usually do not reflect the character's mood but the narrative (such as the climax, for instance). The literature on filters is far scarcer and tends to focus on technical aspects or typical uses rather than on the affective properties of filters [6, 7, 11]. Therefore, this work pursues an approach which does not depend on the existent literature and tries, instead, to learn directly from people mappings from emotions into color.

An evolutionary approach, which relies on genetic algorithms, is used to learn mappings between emotions and color. The focus is on joy and sadness and whether the approach is applicable to other emotions is a topic of future work. Genetic algorithms [12] are appropriate for several reasons. The clear separation between generation and evaluation of alternatives is convenient. Alternatives can be generated using biologically inspired operators - mutation, crossover, etc. Evaluation, in turn, can rely on people. There are several advantages for this: (a) people can be used to fill in the gaps in the literature; (b) a mechanism is introduced to accommodate the biological, individual, and cultural values influencing the perception of emotion in color. Furthermore, the expression space defined by lighting and filters is very

large and genetic algorithms deal well with intractable search spaces.

The paper describes two studies which were conducted to define and understand the mapping of joy and sadness into color. In the first study, subjects are asked to evaluate, as to how well they convey joy or sadness, several images of virtual humans under different configurations of the lighting and filters parameters. The images are presented in sets and each successive set is generated, according to the genetic algorithm, so as to reflect the subject's feedback on the previous set. Subjects are not aware that an evolutionary approach is being used. The purpose of a second study is to try to understand which features characterize the mappings. To accomplish this, images of the best configurations of lighting and filters for joy and sadness are classified according to features that represent color properties (such as average pixel saturation). Statistical tests are then performed to select which features best differentiate the mappings of joy and sadness.

The rest of the paper is organized as follows: Section 2 describes background and related work; Section 3 presents the lighting and filters expression model; Section 4 overviews the evolutionary model; Sections 5 and 6 describe the two studies; and, Section 7 discusses the results and future work.

## 2. Background

It is widely agreed that the nature of the arts is related to the expression of emotions [1, 13, 14, 15]. In one of its simplest conceptions, art is seen as the expression of the artist's feelings [13, 14]. However, Hospers [1] refined this view by noting that the work of art need not reflect the emotions of its creator but can be said to possess emotional properties in its own right. Thus, first, the creator manipulates the formal elements of art (line, space, mass, light, color, texture, pattern, sound and motion) to convey felt or imagined emotions. Then, the audience relies on analogies with the internal and external manifestations of emotions they experienced in the past to interpret the work of art.

This insight motivates going beyond the usual channels of expression in virtual humans, i.e., gesture, face and voice [13], and use the elements of art to express emotions. This insight has been explored in the work of de Melo and Paiva. In a first system [17], they define simple rules which manipulate the camera, lights and music to reflect the emotional state of characters in a story. The lighting rules, in particular, rely on simple associations of emotions to colors (e.g., yellow reflects joy) which are unlikely to generalize [3]. In a second system [18], they integrate filters and a sophisticated lighting model with a virtual human platform that supports the usual bodily channels of expression. The system also allows definition of rules mapping emotions into appropriate lighting and filters. However, no mapping for the expression of emotions is actually proposed. This paper picks up where they left off and proposes a method to learn such mappings and presents

a concrete mapping for joy and sadness.

The mappings associate emotions with color. Color, in turn, is controlled by manipulation of lighting and filters. Lighting is the deliberate control of light to express, among other things, emotions [5, 6, 9, 10]. To achieve these goals, the following parameters are usually manipulated: light type, direction, source color, intensity, softness, decay, throw pattern, shadow softness and shadow size. In this paper a genetic algorithm is going to be used to traverse a subset of this parameter space. However, several other approaches have been explored. In the inverse lighting approach [19] the artist defines partially the scene illumination and the system has to work backwards to establish the missing parameters. Representative is the system by Pellacini et al. [20] where the artist paints lighting into the scene using a typical painting program interface and the system calculates the lighting parameters. The approach in this paper differs in that it seeks to capture intuitions (about the expression of emotions using lights) from regular people, as opposed to lighting artists. The system is responsible for generating the alternatives, which a non-artist is unlikely to be proficient in doing, and the user is only responsible for evaluating them (as to how well they convey an emotion). Another line of research proposes lighting models for interactive virtual worlds based on film and theater literature [21, 22]. These models are constrained by the limitations of the existent literature which does not detail how can light express a particular emotion, nor how the interpretation of light varies with biology, individual and culture. The approach described in this paper differs in that lighting design is learned directly from people thus, providing an empirical method which addresses the limitations in the literature. This approach is particularly useful in understanding the affective interpretation of filters, of which little has been written. Filters manipulate the virtual human pixels themselves to express, among other things, emotions [6, 7, 11]. A filter is a user-defined program which post-processes the pixels in a rendered image [8]. Filters have many advantages: they are efficient as they are independent of the scene geometry; they are very expressive due to the variety of available filters [23]; and, they can be concatenated to create compound effects.

An evolutionary approach is proposed to learn how to map emotions into color. To the best of our knowledge, there is no prior attempt to use evolutionary algorithms to express emotions in virtual humans. Nevertheless, they have been widely explored in other areas. Karl Sims [24] explores a genetic programming approach using symbolic lisp expressions to generate images, solid textures and animations. The artist Steven Rooke [25] uses a set of low and high-level primitives to guide his genetic programming approach to generate images within his own style. Contrasting to the previous approaches, genetic algorithms have been used to evolve shaders [26], fractals [27] and complex three-dimensional objects [28]. In all these systems the

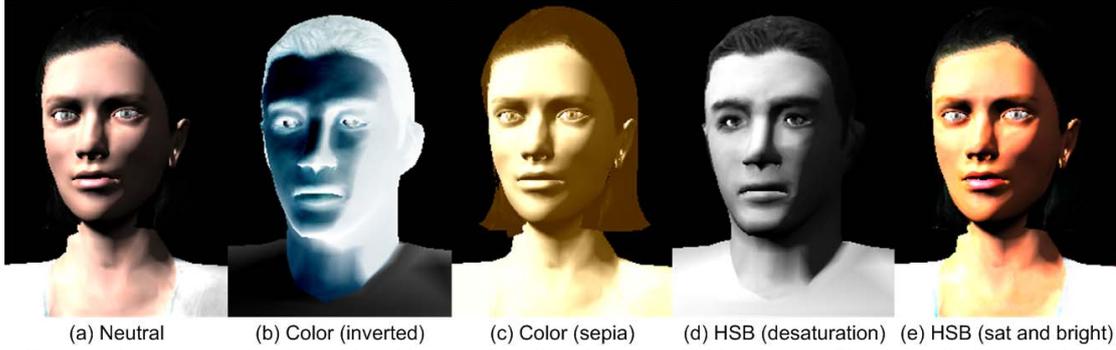


Figure 1: Filters used to post-process the rendered image of the illuminated virtual human. No filter is applied in (a). The color filter is used to invert the colors in (b) and create the sepia look in (c). The HSB filter is used to reduce saturation in (d) and to increase the saturation and brightness in (e). Both virtual humans used in this work are shown.

human, assuming the role of a critic, interactively guides the evolution process.

### 3. The Expression Model

The lighting model defines local pixel-level illumination of the virtual human. Among the supported parameters, the following are used in this work: (a) *type*, defines whether the light source is directional, point or spotlight; (b) *direction*, defines the illumination angle; (c) *ambient*, *diffuse* and *specular colors*, define the light color for each component. Color can be defined in either RGB (red, green, blue) or HSB (hue, saturation, brightness) spaces [4]; *ambient*, *diffuse* and *specular intensity*, define a value which is multiplied with the respective component color. Setting the value to 0 disables the component.

Filters are used to post-process the pixels of the illuminated rendered image of the virtual human. Several filters are available in the literature [23] and this work uses the following subset: the *color* filter, Fig.1-(b) and (c), sets the virtual human's color to convey a stylized look such as black & white, sepia or inverted colors; the *HSB* filter, Fig.1-(d) and (e), manipulates the virtual human's hue, saturation or brightness. Filters can also be concatenated to create compound effects.

### 4. The Evolutionary Model

Building on the expression model, the evolutionary model uses genetic algorithms to evolve, for a certain emotion, a *population of hypotheses*, which define specific configurations of lighting and filters parameters. Evolution is guided by feedback from the user as to how well each hypothesis conveys the intended emotion. The *fitness function*, in this case, is the subjective criteria of the user.

At the core lies a standard implementation of the genetic algorithm [12]. The algorithm is characterized by the following parameters: (a) stopping criteria to end the algorithm, i.e., the maximum number of iterations; (b) the size of the population,  $p$ , to be maintained; (c) the selection method,  $sm$ , to select probabilistically among the hypotheses in a population when applying the genetic operations. Two methods are supported:

*roulette wheel*, which selects a hypothesis according to the ratio of its fitness to the sum of all hypotheses' fitness; *tournament selection*, which selects with probability  $p'$  the most fit among two hypotheses selected using roulette wheel; (e) the crossover rate,  $r$ , which defines the percentage of the population subjected to crossover; (f) the mutation rate,  $m$ , which defines the percentage of the population subjected to mutation; (g) the elitism rate,  $e$ , which defines the percentage of the population which propagates unchanged to the next generation. The rationale behind elitism is to avoid losing the best hypotheses from the previous population in the new population [12].

The algorithm begins by setting up the initial population with random hypotheses. Thereafter, the algorithm enters a loop, evolving populations, until the stopping criterion is met. In each iteration, first,  $(1-r)p$  percent of the population is selected for the next generation; second,  $r*p/2$  pairs of hypotheses are selected for crossover and the offspring are added to the next generation; third,  $m$  percent of the population is randomly mutated; fourth,  $e$  percent of the hypotheses is carried over unchanged to the next generation. Evaluation is based on feedback from the user.

The hypothesis is structured according to the lighting and filter parameters. Lighting uses the common three-point configuration [5, 6] which defines a primary key light and a secondary fill light. The backlight is not used in this work. Both lights are modeled as directional lights and are characterized by the following parameters: (a) *direction*, corresponds to a bi-dimensional floating-point vector defining angles about the  $x$  and  $y$  axis with respect to the camera-character direction. The angles are kept in the range  $[-75.0^\circ, 75.0^\circ]$  as these correspond to good illumination angles [5]; (b) *diffuse color*, corresponds to a RGB vector; (c)  $K_d$ , defines the diffuse color intensity in the range  $[0.0, 5.0]$ ; (d)  $K_s$ , defines the specular color intensity in the range  $[0.0, 3.0]$ . The HSB and color filters are also applied to the virtual human. Thus, four more parameters are defined: (a) *HSB.hue*, *HSB.saturation* and *HSB.brightness*, define the HSB filter's hue (in the range  $[0.0, 10.0]$ ), saturation (in the range  $[0.0, 5.0]$ ) and brightness (in the range  $[0.5, 3.0]$ ); (b) *color.style*, which defines whether to apply the black

& white, sepia or inverted colors style for the color filter. Both filters can be applied simultaneously.

## 5. Study 1: Evolving a Mapping for Joy and Sadness

In a first study, subjects evolve mappings for joy and sadness. The experiment is designed so that subjects are unaware that genetic algorithms are being used. They are asked to classify five ‘sets’ (i.e., populations) of ‘alternatives’ (i.e., hypotheses) for the expression of each emotion. Classification of alternatives goes from 0.0 (‘the image does not express the emotion at all’ or low fitness) to 1.0 (‘the image perfectly expresses the emotion’ or high fitness). The sets are presented in succession, being the first generated randomly and the succeeding ones evolved by the genetic algorithm.

The experiment is automated in software. The user can save the session and continue at any time. A random name is given to the session so as to preserve anonymity. The parameters for the genetic algorithm are:  $p = 30$ ,  $sm = \textit{tournament selection}$ ,  $r = 0.70$ ,  $m = 0.15$  and  $e = 0.10$ . Two virtual humans are used: a male and a female. The rationale for using multiple virtual humans is to minimize geometry effects in the analysis of the results (e.g., the illusion of a smile under certain lighting conditions even though no smile is generated). Participants are evenly distributed among virtual humans. The virtual human assumes the anatomical position and Perlin noise and blinking is applied. No gesture, facial or vocal expression is used throughout the whole experiment. Transition between hypotheses is instantaneous. The camera is fixed and frames the upper body of the virtual human.

The study was mostly conducted in person at the University of Southern California campus and related institutions but, the software was also published in the web. Thirty subjects were recruited. Average age was 26.7 years, 46.7% were male, mostly having superior education (93.3% college level or above) in diverse fields. All subjects were recruited in the United States, even though having diverse origins (North America: 50.0%; Asia: 20%; Europe: 20%; South America: 6.7%). Average survey time was around 20 minutes.

The evolution of the average population fitness for joy and sadness is shown, respectively in Tables 1 and 2. Fourteen (out of possible thirty) of the highest fit hypotheses, one per subject, for joy and sadness are shown in Figures 2 and 3, respectively.

Table 1: Average fitness per set for joy.

	AVG	STD	L	U
Set 1	0.226	0.101	0.190	0.262
Set 2	0.278	0.123	0.233	0.322
Set 3	0.318	0.144	0.266	0.369
Set 4	0.326	0.152	0.271	0.380
Set 5	0.347	0.140	0.296	0.397

AVG - average classification; STD - standard deviation; L and

U - lower and upper bounds for the 95% confidence interval.

Table 2: Average fitness per set for sadness.

	AVG	STD	L	U
Set 1	0.315	0.193	0.246	0.384
Set 2	0.397	0.171	0.335	0.458
Set 3	0.433	0.185	0.367	0.499
Set 4	0.467	0.191	0.399	0.536
Set 5	0.470	0.200	0.399	0.542

AVG - average classification; STD - standard deviation; L and U - lower and upper bounds for the 95% confidence interval.

## 6. Study 2: What are the Features in the Mappings?

The goal of a second study is to understand what features characterize the mappings evolved in the first study. Features refer to characteristics in the image generated by the respective hypothesis. The idea, then, is to differentiate the best images for joy and sadness using these features. These images are the union of, for each emotion, for each subject in the first study, the one with the highest classification. Thus, in total, there are 60 images: the 30 best for joy, one per subject; the 30 best for sadness, one per subject.

From visual inspection of the best images for joy and sadness, four features that measure properties of the pixels are considered: brightness, saturation, temperature and number of colors. The *brightness* of an image is defined, in the range  $[0.0, 1.0]$ , as the average brightness of the pixels. The brightness of a pixel is the subjective perception of luminance in the pixel’s color [4]. The feature is calculated as follows [4]:

$$\textit{Brightness} = \frac{1}{|\textit{Pixels}|} \sum_{p \in \textit{Pixels}} ((R_p + G_p + B_p) / 3) \quad (1)$$

Where: *Pixels* is the set of all pixels in the image;  $(R_p, G_p, B_p)$  is the color of pixel  $p$  and each component is in the range  $[0.0, 1.0]$ .

The *saturation* of an image is defined, in the range  $[0.0, 1.0]$ , as the average saturation of the pixels. Saturation of a pixel refers to the intensity of the pixel’s color [4]. The feature is calculated as follows [4]:

$$\textit{Saturation} = \frac{1}{|\textit{Pixels}|} \sum_{p \in \textit{Pixels}} \frac{1 - \textit{Min}(R_p, G_p, B_p)}{(R_p + G_p + B_p) / 3} \quad (2)$$



Figure 2: Fourteen of the highest fit hypotheses for joy. Each hypothesis is from a different subject.



Figure 3: Fourteen of the highest fit hypotheses for sadness. Each hypothesis is from a different subject.

Where:  $Pixels$  is the set of all pixels in the image;  $(R_p, G_p, B_p)$  is the color of pixel  $p$  and each component is in the range  $[0.0, 1.0]$ .

The *temperature* of an image is defined, in the range  $[1666.7K, \infty]$ , as the average temperature of the pixels. The temperature of a pixel's color refers to the color of a black-body radiator when subjected to a certain temperature and, counter-intuitively, maps lower temperatures to warm colors (yellow-red) and higher temperatures to cool colors (green-blue) [4]. This work uses Robertson's method to compute the temperature of a color [29]. The feature is, then, calculated as follows:

$$Temperature = \frac{1}{|Pixels|} \sum_{p \in Pixels} Robertson(p) \quad (3)$$

Where:  $Pixels$  is the set of all pixels in the image.

The *number of colors* of an image is defined to be the number of different colors in the pixels. However, the maximum number of colors is limited to  $11 \times 11 \times 11 = 1,331$  by rounding the RGB components to one decimal place. Intuitively, this means the feature is only interested in relatively large differences in color.

Having calculated the feature values, the dependent  $t$  test was used to compare means between joy and sadness hypotheses with respect to each feature. The

results are shown in Table 3.

Table 3: Dependent  $t$  test statistics ( $df=29$ ) for difference in means between the joy and sadness images with respect to brightness (BRIG), saturation (SAT), temperature (TEMP) and number of colors (NCOL).

	BRIG*	SAT*	TEMP	NCOL*
Mean Diff.	0.12	0.25	-102.39	199.23
Std. Deviation	0.15	0.29	3443.12	326.14
Std. Err. Mean	0.03	0.05	628.63	59.55
95% CI Lower	0.06	0.14	-1388.07	77.45
95% CI Upper	0.17	0.35	1183.30	321.02
$t$	4.26	4.70	-0.16	3.35
Sig. (2-tailed)	0.00	0.00	0.87	0.00

\* Significant difference,  $p < 0.05$

The results in Table 3 show that:

The average brightness in joy images ( $M=0.36$ ,  $SE=0.02$ ) is higher than in sadness ( $M=0.24$ ,  $SE=0.02$ ,  $t(29)=0.00$ ,  $p < 0.05$ ,  $r=0.62$ );

The average saturation in joy images ( $M=0.44$ ,  $SE=0.04$ ) is higher than in sadness ( $M=0.19$ ,  $SE=0.04$ ,  $t(29)=0.00$ ,  $p < 0.05$ ,  $r=0.66$ );

The average temperature in joy images ( $M=3500.31$ ,  $SE=374.46$ ) is lower than in sadness ( $M=3602.70$ ,  $SE=443.11$ ). But, this difference is not significant ( $t(29)=0.87$ ,  $p > 0.05$ ,  $r=0.03$ );

The average number of colors in joy images ( $M=302.20$ ,  $SE=374.46$ ) is higher than in sadness ( $M=102.97$ ,  $SE=29.93$ ,  $t(29)=0.00$ ,  $p < 0.05$ ,  $r=0.53$ ).

Finally, decision trees [30] were used to classify the 60 images with respect to the four features. The J48 implementation of decision trees in Weka [31] was used with default parameters and 10-fold cross-validation. The resulting tree correctly classifies 47 (78.3%) of the images and is shown in Fig.4.

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NCOLORS <= 26: sadness (23.0/3.0)
NCOLORS > 26
| BRIGHTNESS <= 0.302
| | SATURATION <= 0.413: sadness (7.0)
| | SATURATION > 0.413: joy (10.0/2.0)
| BRIGHTNESS > 0.302: joy (20.0/1.0)

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Figure 4: Decision tree for best joy and sadness images.

## 7. Discussion

This paper argues that color can be used to influence the perception of joy and sadness in virtual humans. To manipulate color, a sophisticated lighting model and filters are integrated with a virtual human platform. Then, an evolutionary model is developed to learn configurations of the lighting and filters parameters which express certain emotions. The model starts with a random set of hypotheses - i.e. configurations of lighting and filters - and, then, uses genetic algorithms to evolve new populations of hypotheses according to feedback provided by people.

In a first study, subjects are asked to evolve mappings for joy and sadness using the evolutionary model. Subjects successively classify five sets of hypotheses, for each emotion, without being informed that a genetic algorithm is being used to generate the sets. The results show that the average set fitness for both emotions is monotonically increasing with each succeeding set (Tables 1 and 2). This suggests that the genetic algorithm is succeeding in providing hypotheses which better express the emotion, according to the subjects' criteria. The fact that subjects are unaware that an evolutionary approach is being used allows us to exclude the possibility that they are classifying latter hypotheses better just because that is what is expected of them in an evolutionary approach. However, the results also show that the average fitness of the fifth and final set is well below the perfect score of 1.0. This might be explained for two reasons: (a) too few sets are being asked to be evolved. This, then, would have been an experimental constraint which existed to limited survey time and not a fundamental limit on the expressiveness of color; (b) no gesture, facial or vocal expression is used. Effectively, these channels have already been shown to play an important role on the expression of emotions in virtual humans [16] and this paper is not arguing otherwise.

A second study analyzes which features characterize the mappings for joy and sadness. Four features are considered: brightness, saturation, temperature and number of colors. The results show that images of joy tend to be brighter, more saturated and have more colors than images of sadness (Table 3 and Fig.4). However, we've only began to explore the collected data and further features reflecting more color properties (e.g., which hues are being used) and the interaction of color with the virtual human's geometry (e.g., the percentage of the face in shadow) should be explored. Our experience also suggests that the focus should be on features reflecting characteristics of the image - i.e., the *phenome* - rather than on parameters of the hypothesis - i.e., the *genome*. There are several reasons for this: (a) subjects are unlikely to be classifying phenomes based on genome features. For instance, a subject is unlikely to be classifying according to the diffuse color or the specular color but, according to the combined effect of the two; (b) similar phenomes can result from different genomes. For instance, a phenome with high brightness can result from high intensity diffuse light as well as from dim diffuse and fill lights plus inversion of colors (with the color filter); (c) preliminary results using decision trees to try to differentiate the best phenomes using only genome features were not promising.

Altogether, these studies suggest that it is possible to express emotions in virtual humans beyond the usual bodily channels - gesture, face and voice. Oatley [32] emphasizes the role the arts play on expression of emotions in humans. The results presented here suggest that the formal elements of art can also play a role on the perception of emotion in virtual humans. Effectively,

if one of the initial motivations for embodied agents was to have more natural interactions with humans [16], what this work suggests is that it is still natural for humans to interact with virtual humans which, aside from the body, use other elements, such as color, to express themselves. The reason this is so still needs further research but one possibility is Hospers's insight that humans perceive emotions in the elements of art because they find analogies to internal and external manifestations of their bodies when experiencing such emotions [1].

Regarding future work, we need to understand how general are the mappings evolved in the first study. The second study already provides some insight on this, in that it suggests features people might be using to differentiate joy and sadness. Moreover, the successful application of a decision tree model, with cross-validation, also suggests that the results might generalize beyond the joy and sadness examples used to generate it. However, ultimately, the mappings need to be validated with people. To do this, it is necessary to setup a careful study where subjects compare images of virtual humans under neutral and emotional conditions. It would also be interesting to explore whether the evolutionary approach generalizes to more emotions. From our experience and the feedback from subjects, we believe this might be so for some, but not all, emotions. Finally, it should be worth exploring whether an approach similar to the one this work takes on color also applies to other formal elements in the visual arts [2].

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## References

1. J. Hospers. *Aesthetics, problems of*. The Encyclopedia of Philosophy, P. Edwards. New York, USA: Ed. Macmillan Publishing Co. 1967.
2. H. Sayre. *A World of Art*, fifth ed. New Jersey, USA: Prentice Hall. 2007.
3. T. Fraser and A. Banks. *Designer's Color Manual: The Complete Guide to Color Theory and Application*. San Francisco, USA: Chronicle Books. 2004.
4. R. Hunt. *The Reproduction of Colour*, Sixth ed. Hoboken, USA: John Wiley & Sons. 2004
5. G. Millerson. *Lighting for Television and film*, 3rd ed. Oxford, UK: Focal Press. 1999.
6. J. Birn. [digital] *Lighting and Rendering*, 2nd ed. California, USA: New Riders. 2006
7. H. Zettl. *Sight, Sound, Motion: Applied Media Aesthetics*. Belmont: Thomson/ Wadsworth. 2008.
8. T. Akenine-Moller, E. Haines and N. Hoffman. *Real-Time Rendering*. Wellesley, USA: AK Peters Ltd. 2009.
9. B. Brown. *Motion Picture and Video Lighting*, 2nd ed. Burlington, USA: Elsevier Inc. 2007.
10. J. Alton. *Painting with Light*. New York, USA: Macmillan Co.. 1949.
11. L. Gross and L. Ward. *Digital Moviemaking*, sixth ed. Belmont, USA: Thomson/Wadsworth. 2007.
12. M. Mitchell. *An Introduction to Genetic Algorithms*, 3rd ed. Massachusetts, USA: MIT Press. 1998.
13. R. Collingwood. *The Principles of Art*. Oxford, UK: Clarendon Press. 1938.
14. L. Tolstoy. *What is Art?* Oxford, USA: Oxford University Press. 1955.
15. R. Elliot. *Aesthetic theory and the experience of art paper*. Proc. of the Aristotelian Society 67, III-26. 1966.
16. J. Gratch, J. Rickel, E. Andre, N. Badler, Cassell, J., E. Petajan: *Creating Interactive Virtual Humans: Some Assembly Required*. IEEE Intelligent Systems. IEEE Computer Society, 17(4): 54–63. 2002.
17. C. de Melo, A. Paiva. *Environment Expression: Expressing Emotions through Cameras, Lights and Music*. Proceedings of Affective Computing Intelligent Interaction (ACII05). 2005.
18. C. de Melo and A. Paiva. *Expression of Emotions in Virtual Humans using Lights, Shadows, Composition and Filters*. Proceedings of Affective Computing Intelligent Interaction (ACII07). 2007.
19. G. Patow and X. Pueyo. *A survey of inverse rendering problems*. Comp. Graphics Forum 22(4):663–687. 2003.
20. F. Pelaccini, F. Battaglia, R. Morley and A. Finkelstein. *Lighting with paint*. ACM Transactions on Graphics 26(2). 2007.
21. M. El-Nasr and I. Horswill. *Automatic lighting design for interactive entertainment*. ACM Computers in Entertainment 2(2). 2004.
22. B. Tomlinson, B. Blumberg and D. Nain. *Expressive autonomous cinematography for interactive virtual environments*. Proceedings of the Fourth International Conference on Autonomous Agents. 2000.
23. St-Laurent, S. *Shaders for Game Programmers and Artists*. Massachusetts, USA: Thomson/Course Technology. 2004.
24. K. Sims. *Artificial evolution for computer graphics*. ACM Computer Graphics 25:319–328. 1991.
25. L. World. *Aesthetic selection: The evolutionary art of Steven Rooke*. IEEE Computer Graphics and Applications 16(1): 4–5. 1996.
26. M. Lewis. *Aesthetic Evolutionary Design with Data Flow Networks*. PhD thesis, Ohio State University. 2001.
27. P. Angeline. *Evolving fractal movies*. Genetic Programming 1996: Proceedings of the First Annual Conference, 503–511. 1996.
28. S. Todd, and W. Latham. *Evolutionary Art and Computers*. San Diego, USA: Academic Press. 1992.
29. A. Robertson. *Computation of Correlated Color Temperature and Distribution Temperature*. Journal of the Optical Society of America, 58(11):1528–1535 (1968)
30. J. Quinlan. *Induction on decision trees*. Machine Learning, 1(1): 813–106. 1986.
31. I. Witten and E. Frank. *Data Mining: Practical machine learning tools and techniques*, 2nd ed. San Francisco, USA: Morgan Kaufmann. 2005.
32. K. Oatley. *Creative expression and communication of emotions in the visual and narrative arts*. In *Handbook of Affective Sciences*, R. Davidson, R. Scherer, and J. Goldsmith (eds.), pp.481–502. New York, USA: Oxford University Press. 2003.