Face-Based Glyphs Revisited

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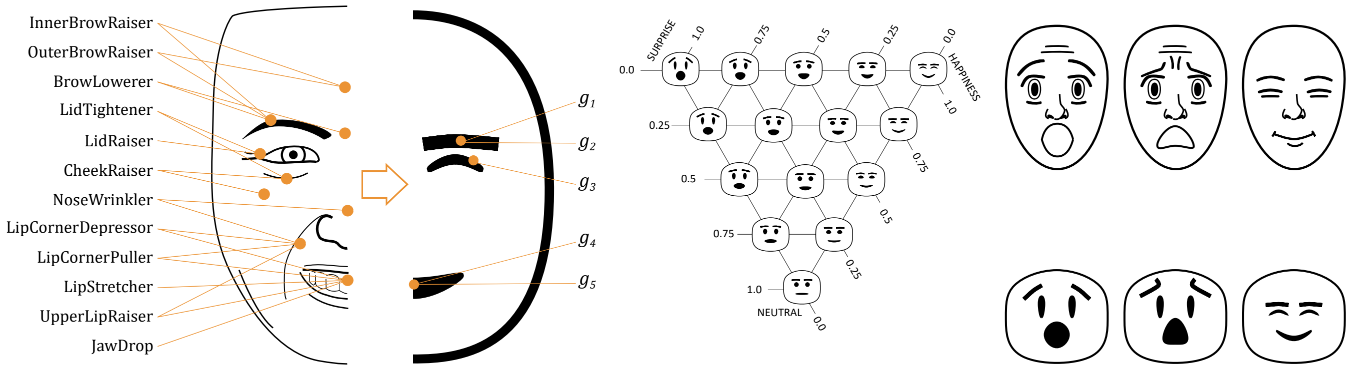

(a) (b) (c) (d)

Figure 1: *Twelve facial actions [EFH02] producing emotions on a human face (a), reduced to the five actions of our 5GU model for emotion glyphs (b). Convex blending of emotions (c), and (d) two realizations of our model for surprise (left), fear (middle), and happiness (right).*

Abstract

While face-based glyphs have known advantages for certain visualization tasks, they suffer from mixing two rather different visual properties of faces: individual traits and emotion expressions. This paper proposes a set of actions on stylized face glyphs that are compatible with psychological evidence embodied in the facial action coding system [EFH02]. It shows how this set can be employed for distinguishing emotion expressions from other facial expressions, and derives an emotion-based glyph space to exploit the pre-attentive processing of emotion expressions. Finally, we report the results of an empirical user study comparing Chernoff-like glyphs with our emotion glyphs in a typical visualization task.

CCS Concepts

• ***Human-centered computing*** → ***Information visualization; Empirical studies in visualization;***

1. Introduction

Face-based glyphs have been studied in the context of multivariate data visualization ever since the seminal paper by Chernoff [Che73]. The cognitive advantage of face-based glyphs lies in the fact that they exploit the pre-attentive processing of facial stimuli provided by the human visual system. While it is well known that Chernoff-like glyphs possess specific advantages, they also exhibit some drawbacks [FIBK17]. A fundamental problem of Chernoff-like glyphs, however, is their undifferentiated combination of permanent facial traits and transient facial expressions. We argue that this combination is potentially confusing and interfering, because the recognition of facial traits and the reading of facial expressions are different cognitive processes. For example, people who perform poorly when it comes to recognizing other people (suffer from prosopagnosia), can perform very well in reading emotions from their faces [DPN03].

In order to gain a better understanding of this potential source of confusion, we study the effects of separating emotion dimensions from the remaining dimensions of face-based glyphs. Facial expressions, including expressions of emotions, have been studied in psychology by Ekman, who created what is now the de facto standard for describing facial expressions, the facial action coding system (FACS) [EFH02]. By applying three types of abstractions to the action units of the FACS, we obtain a set of simplified facial action units for glyphs. Based on this model, we derive an emotion-based subspace for facial glyphs. Additionally, we explore

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our simplified model regarding an assumption on blended emotions motivated by the FACS, according to which, facial expressions of blended emotions are described as convex combinations of the FACS' seven basic emotions. Finally, we evaluate our approach in a user study comparing Chernoff-like glyphs with our emotion glyphs in the typical visualization task of outlier detection.

Our contributions include: (1) We present a model for face-based glyphs consisting of a small set of simplified facial actions that are compatible with the FACS. (2) Based on the convex blending of emotions, we show how to distinguish emotion expressions from non-emotion expressions (grimaces). (3) We report results of a first empirical study, which shows that emotion glyphs generated by the blending process have the potential to outperform Chernoff glyphs in outlier detection. This improved understanding of emotion-related properties of facial glyphs leaves us with essentially two options: using emotion glyphs for tasks where they have advantages, or, subject to future work, refrain from using emotions by deriving a trait-based glyph model with a neutral expression. Our work focuses on the former, which can be based on a well-established descriptive framework for transient facial expressions.

2. Background and Related Work

Fuchs et al. [FIBK17] reviewed visualization techniques for multivariate data and systematically compared them. They conclude that face glyphs outperform other glyph types in certain tasks [Bro85]. McGregor and Slovic [MS86] found that Chernoff faces showed superiority over bar charts, deviation charts, and radar graphs in a rather complex combination of lookup and visual search tasks. In summary, there is evidence that face glyphs can outperform other data glyphs in certain tasks.

Visualizing continuous emotion data has been explored by several researchers. Kovačević et al. [KWS*20] compare two types of glyphs that visualize affective data in three dimensions. They use an abstract glyph design based on the work of Cernea et al. [CWEK15] which encodes emotion through shape and color. Zeng et al. [ZSW*20] propose a visual analytics system for group emotions. They combine a chord diagram and circular bar chart to show the distribution of recognized emotion categories per person. Such types of abstract glyphs, however, cannot take advantage of the pre-attentive processing mechanisms for facial stimuli.

Current examples of research using Chernoff-like face glyphs to visualize data include applications from a wide array of research fields. Publications in civil engineering [GA18], information science [KC17], and software security [VCF*17] have chosen face-based glyphs as their method of information visualization. All three works found Chernoff-like faces to be beneficial for visually analyzing their data. However, they also noted that glyphs showing emotion expressions, such as a smile, biased the visual analysis. Unfortunately, there is no research so far explaining how features of stylized face glyphs link to emotional connotations.

The descriptive framework FACS forms the basis for creating emotion expressions on realistic 3D models of faces [CD19, RTR*11, GDU18]. Such full-screen-sized 3D models, however, provide little help for the design of face-based glyphs, which have to be perceived in a small field of view. The FACS is based on the study of facial expressions of emotions in different cultures. Seven *basic emotions* were found to occur across cultures: surprise, fear, happiness, sadness, disgust, anger, and neutral. The coding system consists of 33 main action units (AUs), each describing the effect of muscular activity on the visual appearance of the face. FACS has been developed as a scientific instrument for capturing the subtlest differences in facial expressions, and requires considerable training (approx. 100 hrs) before it can be employed for classifying facial actions. In information visualization, face-based glyphs are interpreted by untrained observers. We therefore look for a set of AUs that can be distinguished easily even on stylized face glyphs.

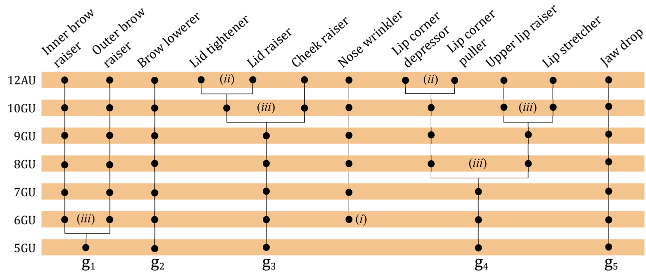

Figure 2: *Abstractions of visual detail (i), antagonistic actions (ii), and close similarity (iii), applied to the set of 12 AUs.*

Many of the facial expressions generated by combinations of AUs do not convey an emotion. For instance, the combination of an angry upper face, a surprised middle face, and a happy lower face produces an expression, which cannot be assigned to an emotion (Figure 3g). For lack of a better term, we call the non-emotion expressions of a face *grimaces*. Later, we will give a formal definition of emotion expressions that separates them from grimaces.

3. Facial Glyph Model

According to the FACS, only 12 AUs are needed for expressing all seven basic emotions, while a single AU may affect more than one visual feature of the face (Figure 1a). In order to clearly distinguish the actions on a stylized glyph from those on a human face, we speak of *glyph units* (GUs), in contrast to the AUs of the FACS.

The abstraction process leading to our simplified facial glyph model (5GU) starts from 12 GUs corresponding to the 12 AUs. Such simplification has, however, a limit, as it should still be possible for untrained observers to recognize the basic emotions. Thus, the abstraction principles have to find a balance between simplifying the glyph units to support display on a small visual area, and simplifying them too much, which would make the emotion content hard or impossible to decode. Application of the following abstractions results in our set of five GUs (our 5GU model), as presented in Figure 1b and Table 1. Figure 2 illustrates this abstraction process.

Abstraction of visual detail. GUs that only affect facial features with high level of visual detail in the glyph, e.g., furrows and wrinkles or the nose, are left out of the final set of GUs, since even skilled FACS coders sometimes miss such facial actions [EFH02].

Abstraction of antagonistic actions. Some GUs work in pairs, such as the ones causing smiling and frowning. This abstraction combines two antagonistic GUs into a single one, which does not cause a problem, since they cannot co-occur.

Abstraction of close similarity. The FACS manual explicitly lists pairs of facial actions that only show "subtle differences". GUs that are likely to be confused, are combined into a single abstract GU.

The intensity of muscular activity causing facial actions varies continuously, and is thus described by a continuous value, bounded by a minimum and maximum. In the 5GU model, this range is rescaled to $[0,1]$ for all GUs, except the GUs that combine antagonistic actions, which are rescaled to $[-1,1]$. Formally, a facial glyph in our 5GU model is specified by a vector $\vec{g} \in \Omega \subset \mathbb{R}^5$, the components of which correspond to intensities of the five GUs (Table 1).

The GU vectors $\vec{g}$ of the 5GU model describe actions upon a facial glyph, but are not sufficient to determine the visual appearance of the glyph consisting of a number of graphical features, such as the eyes or the mouth, including features that are not affected by the GUs, such as ears or hair. In order to render a facial glyph, a graphical realization of the 5GU model must first provide the visual appearance of the selected facial features of the glyph. It is convenient to model these facial features by parametrized 2D geometry, such as cubic splines or Bézier curves. Thus, for each of the five GUs, we define how their intensity moves the control points of the respective geometrical model.

Figure 1d shows two—both in level of detail and number of facial features—vastly different graphical realizations of the 5GU model we created. The left two glyphs show two graphical implementations of the basic emotion of surprise with the mouth affected by the GUs 'mouth frowner smiler' with $g_4 = 0$ and 'jaw drop' with $g_5 = 1$ (Table 1). Similarly, the middle two glyphs show the fear mouth with the GUs $g_4 = -1$ and $g_5 = 1$, and the right two show happiness with $g_4 = 1$ and $g_5 = 0$. The simpler (bottom row) of the two implementations models the mouth and eyes as closed cubic B-splines with four control points each, and the brows as cubic cardinal splines with three control points each. The axes along which each GU moves the control points, are illustrated in Figure 3h and i. Note that the shapes' contours have a width, which is why parts of the closed curves may appear to lie outside the control polygons (dashed in Figure 3h and i).

4. Emotion Expressions and Grimaces

The 5GU model offers five degrees of freedom to visualize data, by the intensities of the five GUs. With the intensity ranges from

Table 1: *GUs g_1 (brow raiser), g_2 (brow lowerer), g_3 (eye squinter opener), g_4 (mouth frowner smiler), and g_5 (jaw drop) in the 5GU model, and the GU vectors of the seven basic emotions happiness $\vec{h}$, fear $\vec{f}$, anger $\vec{a}$, sadness $\vec{s}$, disgust $\vec{d}$, surprise $\vec{u}$, and neutral $\vec{n}$.*

GU	Description	Intensity	$\vec{h}$	$\vec{f}$	$\vec{a}$	$\vec{s}$	$\vec{d}$	$\vec{u}$	$\vec{n}$
g_1	pulls the brows up	$[0,1]$	0	1	0.5	1	0	1	0
g_2	pulls the brows together	$[0,1]$	0	1	1	1	1	0	0
g_3	squints or opens the eyes	$[-1,1]$	-1	1	0	0	-1	1	0
g_4	pulls lip corners down or up	$[-1,1]$	1	-1	-1	-1	-1	0	0
g_5	opens the mouth	$[0,1]$	0	1	0.5	0	0	1	0

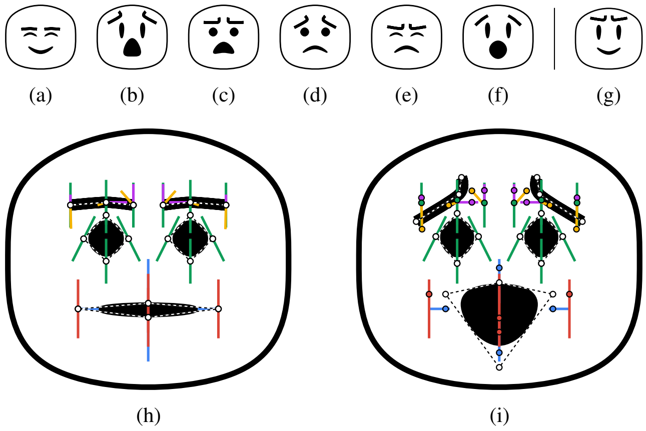

Figure 3: *Implementation of the 5GU model showing happiness (a), fear (b), anger (c), sadness (d), disgust (e), surprise (f), and a grimace (g). Simplified geometric model with (h) neutral expression $g_1 = 0$ (yellow), $g_2 = 0$ (purple), $g_3 = 0$ (green), $g_4 = 0$ (red), $g_5 = 0$ (blue), and with (i) moved control points $g_1 = 1.0$, $g_2 = 0.7$, $g_3 = 0.1$, $g_4 = 0.5$, $g_5 = 0.8$.*

Table 1, the five GUs define a hypercuboid Ω in $\mathbb{R}^5$, which contains the zero vector. All vectors in Ω denote facial expressions—however, they do not all represent emotions. This is no surprise, as the human face can form grimaces without emotional connotation.

While the FACS determines the number of basic emotions, it does not specify their respective intensities. However, we obtain coordinates of the basic emotions in the 5GU model from constraints specified by that coding system. At zero intensity of all GUs, the face shows the neutral emotion. The other basic emotions mostly involve facial actions at their maximum or minimum intensity, resulting in the coordinates shown in Table 1. Visual inspection of Figure 3a–f shows that the resulting glyphs are compatible with the FACS description of the basic emotion expressions.

Since there are seven basic emotions including neutral, and since the 5GU model has only five GU dimensions, it is not possible that all seven basic emotions are linearly independent in the 5GU model (for the GU vectors of Table 1, we find $\mathrm{rank}(\vec{h}, \vec{f}, \vec{s}, \vec{d}, \vec{u}, \vec{a}) = 5$). Further analysis of the basic emotions' GU vectors shows that the basic emotions $\vec{h}, \vec{f}, \vec{s}, \vec{d}, \vec{u}, \vec{n}$ form a simplex that contains the origin ($\vec{n} = \vec{0}$), with anger being colinear to fear and disgust ($\vec{a} = 0.5\vec{f} + 0.5\vec{d}$). The dependence of anger on fear and disgust is supported by the fact that blending expressions of fear and disgust comes very close to an expression of anger [EF03].

The FACS describes the blending of basic emotions, but does not give a fully fledged account of it. The following assumptions are consistent with the constraints of the coding system. Given a basic emotion's GU vector $\vec{g}$ and any $0 \leq \alpha \leq 1$, the resulting vector $\alpha\vec{g}$ is a GU vector of an emotion expression. Such a multiplication with a scalar $0 \leq \alpha \leq 1$ simply denotes the basic emotion $\vec{g}$ with a reduced intensity. An alternative way to describe an emotion expression $\alpha\vec{g}$ with diminished intensity consists in writing it as linear combination of $\vec{g}$ with the neutral emotion $\vec{n} = \vec{0}$, with weights adding up to 1. The blending of surprise and neutral in Figure 1c illustrates this.

This generalizes to the case of two or more basic emotions, and permits blends of any number of linearly independent basic emotions and neutral. The blended emotion $\vec{g}$ is expressed as a convex combination of the linearly independent subset of basic emotions $\{\vec{h}, \vec{f}, \vec{s}, \vec{d}, \vec{u}\}$. Figure 1c shows a barycentric map of blending surprise, happiness, and neutral, generated from the 5GU model.

In other words, given the 5-simplex formed by the GU vectors of the six emotion expressions $\vec{h}, \vec{f}, \vec{s}, \vec{d}, \vec{u}, \vec{n}$, the barycentric coordinates of any blended emotion expression $\vec{g}$ are given as:

$$\vec{g} = \alpha_1 \vec{h} + \alpha_2 \vec{f} + \alpha_3 \vec{s} + \alpha_4 \vec{d} + \alpha_5 \vec{u},$$

with $\sum_{i=1}^{5} a_i = 1$ and $a_i \geq 0$. With this definition, we are in a position to distinguish emotions and grimaces in the 5GU model. A GU vector $\vec{g}$ encodes an *emotion expression* if and only if it is contained in that simplex of basic emotions. The barycentric coordinates provide a simple criterion for testing this: if the barycentric coordinates of a vector are all nonnegative, then the vector lies within the simplex, otherwise it lies outside.

5. Evaluation

With the 5GU model, we possess the means to generate simplified face-based glyphs and to identify those glyphs that express emotions. We expect the emotion glyphs to exploit the pre-attentive emotion recognition processes of the beholder. More specifically, we expect that outlier detection—the task that Chernoff used to evaluate his face-based glyphs—should be more reliable for emotion glyphs generated from our 5GU model than for Chernoff-like glyphs, because the latter, in addition to the recognition of emotion expressions, require the evaluation of individual facial features.

Design. Our experiment is based on a one-way one-factorial repeated measures design, where the experimental factor is the visualization type. We explore three visualizations: Chernoff-like glyphs (CG), and two implementations of the 5GU model, the simplified (SEG) and the realistic (REG) emotion glyph. We compare the CG to the visually more detailed REG, to ensure that the visual simplicity of the SEG does not pose a confounding factor.

Material. For each visualization type, we create a task made up of 20 trials. Each trial consists of three identical glyphs, plus an outlier and a distractor glyph displayed in a row in random order (Figure 4a). We used the 5GU model to generate SEG and REG that represent emotions. The CGs with five DOFs were generated from the same 5D data vectors as the SEG and REG. The encoding of the five data dimensions in the CG ensures fair conditions by matching the encoding of the emotion glyphs, e.g., the value of g_5 (jaw drop) in the SEG and REG to mouth size in the CG. The outlier differs from the remaining identical glyphs in two facial features (CG) or facial actions (SEG, REG), while the distractor differs only in one.

Participants and Procedure. 25 participants (6 female, 19 male) aged from 17 to 45 ($\mu = 26.19$, $\sigma = 6.81$) were presented the outlined outlier detection task for each of the three glyph types. For each participant, we calculated the correctness, i.e., the proportion of identified outliers to number of trials for each glyph type.

Results. On average, the participants found the most outliers in the SEG ($\mu = 0.49$, $\sigma = 0.11$), closely followed by the REG ($\mu = 0.45$, $\sigma = 0.15$). They identified fewer correct outliers for the CG ($\mu = 0.36$, $\sigma = 0.12$) (Figure 4b). An ANOVA shows that the correctness rate was significantly affected by the type of glyph, ($F(2, 48) = 13.35$, $p < 0.001$, and $\eta^2 = 0.16$). This corresponds to a medium large effect. Post-hoc Bonferroni tests revealed significant differences between the CG and both the SEG ($p < 0.0001$, $d = 1.14$), and the REG ($p = 0.02$, $d = 0.64$). The SEG had a mean over one standard deviation larger than the CG. The difference between SEG and REG, however, was not significant ($p = 0.33$, $d = 0.34$).

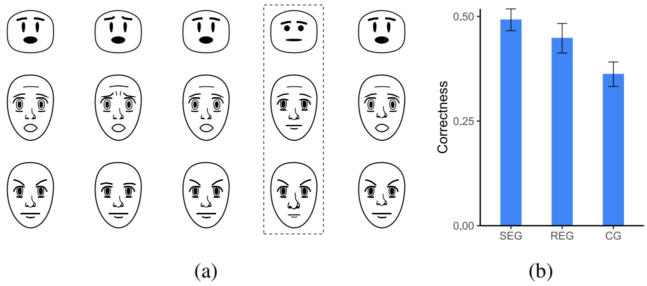

Figure 4: *For each row of five glyphs (a) in the three visualizations SEG (top), REG (middle), and CG (bottom), participants had to identify the outlier (dashed). (b) Average correctness of answers.*

Discussion. In the experiment, outliers were identified more reliably for the emotion glyphs (SEG, REG) generated from our 5GU model than for the Chernoff-like glyphs (CG). We interpret this as first evidence supporting the hypothesis that it is easier to process emotion-only glyphs than Chernoff-like glyphs, which, in contrast to our approach, unintentionally combine emotions and facial traits. While the size of the effect found is remarkable, further studies are needed to elucidate the exact conditions under which it occurs.

6. Conclusion

With the 5GU model, we have identified a small set of actions on stylized face glyphs that is compatible with the psychological evidence from the facial action coding system FACS. By representing blended emotions as convex combinations of basic emotions, we showed how to distinguish emotion expressions from grimaces: emotion expressions are the GU vectors within the simplex formed by the basic emotions, leading to our emotion glyphs. Finally, we evaluated our approach in an experiment comparing Chernoff glyphs with emotion glyphs generated from the 5GU model, finding an advantage for our emotion glyphs. We conclude that the 5GU model has the potential to improve facial glyphs, since it permits to isolate visual variables expressing emotions from the remaining facial features. For visualization of data with up to five dimensions, one could opt for emotion glyphs, while excluding all emotion expressions, except neutral from Chernoff glyphs, may be better suited for more data dimensions. Such exclusion would, however, need to be subject of future work.

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References

[Bro85] BROWN R.: Methods for the graphic representation of systems simulated data. *Ergonomics 28*, 10 (1985), 1439–1454. 2

[CD19] CUCULO V., D'AMELIO A.: OpenFACS: an open source FACS-based 3D face animation system. In *International Conference on Image and Graphics* (2019), Springer, pp. 232–242. 2

[Che73] CHERNOFF H.: The use of faces to represent points in k-dimensional space graphically. *Journal of the American statistical Association 68*, 342 (1973), 361–368. 1

[CWEK15] CERNEA D., WEBER C., EBERT A., KERREN A.: Emotion-prints: Interaction-driven emotion visualization on multi-touch interfaces. In *Proc. Visualization and Data Analysis* (2015), vol. 9397, p. 93970A. 2

[DPN03] DUCHAINE B. C., PARKER H., NAKAYAMA K.: Normal recognition of emotion in a prosopagnosic. *Perception 32*, 7 (2003), 827–838. 1

[EF03] EKMAN P., FRIESEN W. V.: *Unmasking the face: A guide to recognizing emotions from facial clues*, vol. 10. ISHK, 2003. 3

[EFH02] EKMAN P., FRIESEN W. V., HAGER J. C.: *Facial action coding system: The Manual*. Consulting Psychologists Press, 2002. 1, 2

[FIBK17] FUCHS J., ISENBERG P., BEZERIANOS A., KEIM D.: A systematic review of experimental studies on data glyphs. *IEEE Transactions on Visualization and Computer Graphics 23*, 7 (2017), 1863–1879. 1, 2

[GA18] GUHA A. H., ASSAF G. J.: Representing collected road condition data with chernoff faces for evaluation of pavement conditions. In *Proc. Civil Infrastructures Confronting Severe Weathers and Climate Changes Conference* (2018), Springer, pp. 136–150. 2

[GDU18] GILBERT M., DEMARCHI S., URDAPILLETA I.: FACSHuman a software to create experimental material by modeling 3D facial expression. In *Proceedings of the 18th international conference on intelligent virtual agents* (2018), pp. 333–334. 2

[KC17] KIM Y.-S., COOKE L.: Big data analysis of public library operations and services by using the chernoff face method. *Journal of Documentation 73*, 3 (2017), 466–480. 2

[KWS*20] KOVACEVIC N., WAMPFLER R., SOLENTHALER B., GROSS M., GÜNTHER T.: Glyph-based visualization of affective states. In *Proc. Eurographics Conference on Visualization – Short Papers* (2020), Eurographics Association, pp. 121–125. 2

[MS86] MACGREGOR D., SLOVIC P.: Graphic representation of judgmental information. *Human-Computer Interaction 2*, 3 (1986), 179–200. 2

[RTR*11] ROESCH E. B., TAMARIT L., REVERET L., GRANDJEAN D., SANDER D., SCHERER K. R.: FACSGen: A tool to synthesize emotional facial expressions through systematic manipulation of facial action units. *Journal of Nonverbal Behavior 35*, 1 (2011), 1–16. 2

[VCF*17] VANHOUDNOS N., CASEY W., FRENCH D., LINDAUER B., KANAL E., WRIGHT E., WOODS B., MOON S., JANSEN P., CARBONELL J.: This malware looks familiar: Laymen identify malware run-time similarity with chernoff faces and stick figures. In *Proc. of EAI International Conference on Bio-inspired Information and Communications Technologies* (2017). 2

[ZSW*20] ZENG H., SHU X., WANG Y., WANG Y., ZHANG L., PONG T.-C., QU H.: Emotioncues: Emotion-oriented visual summarization of classroom videos. *IEEE Transactions on Visualization and Computer Graphics 27*, 7 (2020), 3168–3181. 2