Human Emotion and the Uncanny Valley: A GLM, MDS, and Isomap Analysis of Robot Video Ratings

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ABSTRACT

The eerie feeling attributed to human-looking robots and animated characters may be a key factor in our perceptual and cognitive discrimination of the human and humanlike. This study applies regression, the generalized linear model (GLM), factor analysis, multidimensional scaling (MDS), and kernel isometric mapping (Isomap) to analyze ratings of 27 emotions of 18 moving figures whose appearance varies along a human likeness continuum. The results indicate (1) Attributions of *eerie* and *creepy* better capture our visceral reaction to an uncanny robot than *strange*. (2) Eerie and creepy are mainly associated with *fear* but also *shocked, disgusted,* and *nervous.* Strange is less strongly associated with emotion. (3) Thus, strange may be more cognitive, while eerie and creepy are more perceptual/emotional. (4) Human features increase ratings of human likeness. (5) Women are slightly more sensitive to eerie and creepy than men; and older people may be more willing to attribute human likeness to a robot despite its eeriness.

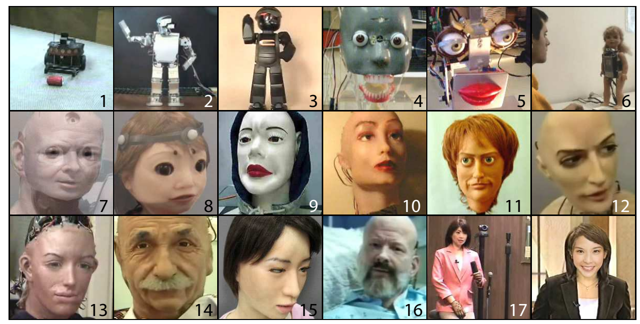

Figure 1: Participants rated video clips of 17 robots of varying human likeness and 1 human by showing their level of agreement with 27 emotion-related statements and 4 statements related to eeriness, creepiness, strangeness, and human likeness.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioral Sciences—*psychology*; H.1.2 [**Information Systems**]: User/ Machine Systems—*human information processing*

General Terms

Human Factors

Keywords

Android science, emotion, data visualization, uncanny valley

1. INTRODUCTION

In recent years socially-assistive robots have demonstrated their ability to help people in everyday life, from encouragement in performing rehabilitation exercises to companionship and social mediation [2] [3] [6] [20] [21]. Meanwhile, android robots are simulating human form, motion quality, and contingent interaction with increasing realism [7] [9] [8] [10]. Given the human desire for companionship and for nurturing others [20], which is linked to our biological imperative, it is not hard to foresee the widespread use of humanlike robots once certain issues are resolved.

One of these issues is the uncanny valley (*bukimi no tani* in Japanese). In 1970 Masahiro Mori, a Japanese robotics pioneer, proposed a hypothetical graph that predicted that the more human a robot looks, the more familiar it is, until a point is reached at which subtle imperfections make the robot seem eerie [11] [9]. This 'dip' appears just before total human likeness. Dead bodies are an example Mori gives of something that inhabits the uncanny valley.

Mori proposed that the eeriness of human-looking robots has to do with self-preservation. In this vein Christian Keysers has proceeded to explain the uncanny valley from an evolutionary perspective [9]. Drawing on Rozin's theory [16], Keysers proposed the phenomenon could be associated with disgust—an evolved cognitive mechanism for pathogen avoidance. The idea is that the more closely another organism is related to us genetically, the higher the probability it will be carrying transmissible bacteria, viruses, and other parasites. Thus, we are most sensitive to signs of disease in our own species and least sensitive in species that are

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only distantly related. Others have also proposed a relation between the uncanny valley and evolutionary aesthetics [9]: given the selective pressures on our ancestors to mix their genes with the genes of those who could maximize the number and fitness of their progeny, perceptual sensitivity to indicators of low fertility or a weak immune system could be responsible for the evolution of mechanisms underlying feelings of eeriness toward human forms that are sufficiently far from biological ideals.

In a previous experiment, a photograph of an android made disturbing by pulling the eyes back from the face elicited the subconscious activation of death-related associations [9] (Robot 15 in Fig. 1). In addition, it elicited psychological defenses toward those who threatened the participants' worldview, which manifested in a less favorable attitude toward foreign students who criticized the participants' home country in the group exposed to the android as compared with the control group. This experiment suggests that an uncanny robot may elicit an innate fear of dying and psychological defenses for coping with the inevitability of death [4], an idea first proposed by Sara Kiesler [9]. However, as these terror management defenses can operate in the absence of emotion [18], their relation to eeriness needs to be clarified.

Androids have the potential to trigger other repressed fears. Having an android *Doppelganger* may elicit a fear of being replaced. Human-looking robots—especially if they could one day rival human intelligence—raise the question of whether we might not all just be soulless machines. The jerkiness of a robot's movements could lead to a fear of losing body control. The cognitive dissonance caused by an entity that lies between familiar categories—electromechanical in nature but human in appearance—could also be a factor in the uncanny valley, especially when one of those categories is our own personal and human identity [14].

However, there have not been any empirical studies that have determined to what extent the eeriness of humanlike robots is rooted in emotion and which emotions are implicated in this kind of eeriness. In addition, past studies have tended to use still images for stimuli, neglecting the relation between eeriness and motion quality (e.g., jerkiness), timing, and other aspects of contingent interaction.

There is also some concern about what the appropriate dependent variable is in Mori's graph of the uncanny valley. The familiarity axis he originally proposed has not been widely accepted, perhaps partly because it is difficult to define negative familiarity, because it implausibly lies beyond total novelty. So the question remains whether strangeness or eeriness is the most appropriate counterpoint to familiarity. (*Strange* is a typical term for describing the unfamiliar.)

There is no consensus on what emotions are—for example, psychological kinds, physiological states, dispositions to behave, evolutionary adaptations, social constructs, or some combination of these [5]. So there is certainly no consensus on how to measure them. While we would advocate a convergent approach that compares data from various sources, such as physiological readings and realtime interaction, to simplify the design of this study, self-reports are used. The risk with self-reports—or any other method—is that what is being measured may not correspond to the putative inner constructs (emotions) to be measured.

Within these limitations this study explores the relation between the uncanny valley and human emotion by analyzing participant ratings of video clips of robots that vary in form and motion quality from mechanical to almost human. Although the use of videos precludes the study of contingent interaction, it does enable us to work with participants in Indonesia who had little or no prior exposure to robots. This was valuable because anecdotal evidence indicates that the eeriness of a human-looking robot habituates with exposure: People can become accustomed to a robot (or other entity) that at first gave them chills. Studies on the uncanny valley not only benefit the field of human-robot interaction, offering design principles for building robots to which people can better relate, but also deepen the understanding of perceptual mechanisms in cognitive psychology.

1.1 Research Questions

RQ1. When observing active robots, what emotion terms are related to attributions of eerie, creepy, and strange?

RQ2. To what extent are these terms rooted in earlier ('perceptual') or later ('cognitive') processing and how does this involve emotion?

RQ3. Does *eerie, creepy,* or *strange* better describe uncanny robots, and how are these terms different?

RQ4. Do age, sex, and specific features of a robot's appearance affect perception?

RQ5. What features of a robot's appearance are associated with human likeness?

2. METHODS

2.1 Participants

There were 143 Indonesian participants, 103 male and 40 female, of whom 35 were 17 to 20 years old (17 being the age of majority), 85 were 21 to 25, 16 were 26 to 30, 4 were 31 to 35, and 3 were 36 to 40. The participants were mainly university students, young professionals, and government workers. Compared with industrialized societies like Japan, the participants' prior exposure to robots was minimal. Participants were recruited from university clubs and Internet cafes in Jatinangor and Bandung, West Java.

2.2 Materials and Procedures

An experimenter assisted with the computer-conducted survey. Each participant viewed each of 18 silent video clips presented one at a time in random order (Fig. 1). There were 17 video clips of robots and one of the woman after whom one of the robots had been modeled. The 200-by-200 pixel clips were displayed on a 14 in. CRT in XVGA mode. Most of the clips were 6 to 12 seconds in length. They were played in a continuous loop while the participant answered a survey on the figure featured in that clip.

The survey consisted of 31 statements and a seven-point Likert scale, ranging from *strongly disagree* to *strongly agree*. For emotion terms, the statements were of the form "The figure makes me feel ______," and the blank was filled with one of 27 emotion terms. In a few cases, alternative statement constructions were used for clarity or because of grammar. For the four other terms, the statements were of the form "The figure looks ______." (Sentences were independently translated from English to *Bahasa Indonesia* and back by two translators. The results were compared with *Kamus* and other Indonesian-English dictionaries, and minor differences in translation were resolved through discussion among the translators and authors.)

Table 1: GLMs for Eerie, Creepy, Strange, and Humanlike by Emotion, Gender, Age, and Robot Features

	Eerie (Standardized Beta)		Creepy (Standardized Beta)		Strange (Standardized Beta)		Humanlike (Standardized Beta)	
	Model E1	Model E2	Model C1	Model C2	Model S1	Model S2	Model H1	Model H2
Fear	$.36^{***}$	$.37^{***}$	$.41^{***}$	$.39^{***}$	$.12^{***}$	$.10^{***}$	$-.08^{**}$	$-.07^{**}$
Shocked	$.13^{***}$	$.13^{***}$	$.15^{***}$	$.15^{***}$	$.16^{***}$	$.18^{***}$	$.14^{***}$	$.11^{***}$
Disgusted	$.12^{***}$	$.12^{***}$	$.14^{***}$	$.12^{***}$	$.14^{***}$	$.13^{***}$	$-.06^{*}$	$-.08^{**}$
Nervous	$.12^{***}$	$.13^{***}$	$.11^{***}$	$.13^{***}$	$.06^{**}$	$.06^{**}$	.04	.01
Dislike	$.09^{***}$	$.08^{***}$	$.07^{***}$	$.06^{***}$	$.18^{***}$	$.18^{***}$	$-.13^{***}$	$-.10^{***}$
Irritated	$.06^{***}$	$.05^{**}$	$.06^{***}$	$.07^{***}$	-.03	$-.04^{\triangle}$	.00	.00
Happy	$-.06^{***}$	$-.05^{**}$	$-.08^{***}$	$-.07^{***}$	$-.13^{***}$	$-.09^{***}$	$.05^{*}$	$.12^{***}$
Relaxed	$-.06^{***}$	$-.06^{***}$	$-.05^{***}$	$-.05^{**}$	$-.13^{***}$	$-.09^{***}$	$.08^{**}$	$.09^{***}$
Worried	$.08^{***}$	$.07^{***}$	.02	.01	$.09^{***}$	$.09^{***}$	$.11^{***}$	$.10^{***}$
Suffering	$.04^{**}$	$.05^{**}$	.00	.01	$-.06^{**}$	$-.05^{*}$	$.05^{*}$	$.05^{*}$
Gender	$-.03^{*}$	$-.03^{*}$	$-.04^{**}$	$-.05^{**}$	-.01	-.01	-.01	.01
Age	.00	.00	-.01	-.01	$.04^{*}$	$.03^{\triangle}$	$.05^{*}$	$.04^{*}$
Mechanical features	-	.02	-	$.06^{*}$	-	$.08^{*}$	-	$.29^{***}$
Human features	-	-.01	-	.01	-	$-.05^{\triangle}$	-	$.52^{***}$
Head shot	-	$.06^{*}$	-	$.09^{**}$	-	$.12^{**}$	-	$.78^{***}$
Adjusted R^2	.61	.61	.62	.61	.36	.33	.08	.33
N	2564	2139	2564	2139	2564	2139	2564	2139

$^{\triangle}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Note: Ratings of the nonhumanoid robot (Robot 1) were used as a baseline. The human woman and redundant ($R > .60$) and nonsignificant ($p > .05$) emotion predictor variables were excluded from the models. *Mechanical features* are defined as Robot 2, 3, and 6; *human features* as Robot 17; and *head shot* as Robot 4, 5, and 7–16.

The emotion terms were amazed, confused, shocked, surprised, curious, irritated, angry, envious, dislike, hate, resentful, disgusted, nauseated, embarrassed, sad, loneliness, suffering, pity, sympathy, fear, nervous, worried, attracted, love, excited, happy, and relaxed. The other terms were eerie (*ngeri* in Indonesian), creepy (*seram*), strange (*aneh*), and humanlike (*seperti manusia*, lit. human-looking). In Indonesian *ngeri* is applied to situations (e.g., "The eerie silence after the bomb exploded in the marketplace"), and *seram* is applied to people (e.g., "The zombie looked creepy"). The survey typically required a little over an hour to complete. In appreciation of their time commitment, a small parting gift was presented as a surprise to participants, including those who quit the study before completing it.

2.3 Statistical analysis and data visualization

Simple multiple linear regression, the general linear model (GLM), and factor analysis were used for statistical analysis and data reduction. Multidimensional scaling (MDS) and isometric feature mapping (Isomap) were used for dimensionality reduction in data visualization.

2.3.1 General Linear Model

The GLM analysis was used to establish regression models that predict ratings of eeriness, creepiness, strangeness, and human likeness while observing each robot. The point is to determine which features of appearance and movement stimulate an emotional reaction correlated with these items.

2.3.2 Factor Analysis

Factor analysis was used to explain the variability in the 31 observed variables in terms of a smaller number of factors. A linear combination of these factors modeled the observed variables. Ideally, these factors correspond to useful concepts.

Table 2: Total Variance Explained

Component	Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	7.80	28.90	28.90
2	3.79	14.04	42.94
3	1.32	4.88	47.82
4	0.68	2.50	50.32

Note: Extraction Method: Maximum Likelihood.

2.3.3 Multidimensional Scaling

MDS created a (Euclidean) distance matrix for all pairs of the 27 emotions and 4 other terms to approximate their distance from each other in a space of reduced dimensionality. It is used in data visualization to explore similarities or dissimilarities in data. MDS postulates that the distance d_{ij} between the i^{th} and the j^{th} stimulus is given by

$$D_{ij} = \sqrt{\sum_{r=1}^{R} (X_{ir} - X_{jr})^2 + S_i + S_j}$$

where X_{ir} is the coordinate of the i^{th} stimulus on the r^{th} dimension and R is the total number of dimensions. In this model, in addition to r common dimensions, the stimuli can have a unique dimension, denoted by S_i, not shared by other stimuli.

Table 3: Rotated Factor Matrix[a]

	Factor			
	1	2	3	4
Hate	**.76**	-.23	.22	.10
Nauseated	**.73**	-.18	.30	.09
Resentful	**.70**	-.19	.33	.13
Disgusted	**.65**	-.21	.32	.19
Irritated	**.64**	-.12	.39	.13
Dislike	**.58**	-.34	.19	.10
Angry	**.56**	-.03	.44	.11
Fear	**.43**	-.20	.42	.36
Happy	-.20	**.79**	-.10	-.08
Excited	-.05	**.77**	-.01	-.04
Relaxed	-.10	**.70**	-.22	.02
Love	-.16	**.69**	.20	-.07
Amazed	-.33	**.57**	.10	-.27
Attracted	-.41	**.51**	-.04	-.26
Sympathy	-.22	**.48**	.01	.20
Curious	-.41	**.46**	.12	.02
Envious	.11	**.42**	.22	.07
Sad	.24	.02	**.66**	.09
Suffering	.39	-.01	**.61**	.10
Loneliness	.16	.10	**.56**	.05
Pity	.06	.02	**.54**	.11
Worried	.22	-.03	**.53**	.27
Nervous	.31	-.03	**.51**	.33
Embarrassed	.27	.19	**.45**	.11
Shocked	.11	.06	.28	**.77**
Surprised	.09	.10	.22	**.75**
Confused	.25	-.14	.30	**.38**

Note: Extraction Method: Maximum Likelihood.
Rotation Method: Varimax with Kaiser Normalization.
[a] Rotation converged in 7 iterations.

2.3.4 Kernel Isometric Feature Mapping

Isomap estimates the geodesic distance between all pairs of data points along a manifold and then uses classical multidimensional scaling to construct an embedding of lower dimensionality [19]. The algorithm has four steps:

1. Calculate the distance between all data points $\delta_{ij} = \sqrt{(X_i - X_j)^2}$.

2. Construct a neighborhood graph, which includes edge $ij \in G$ (e.g., if i is a K-nearest neighbor of j), and assign the weight δ_{ij} to edge ij.

3. Compute (by Dykstra's algorithm) the shortest path distance d_{ij} between all pairs of nodes in G.

4. Apply MDS to the shortest-path distance matrix $\{d_{ij}\}$ to construct Y_j, a lower dimensional embedding of the data.

The main advantage of Isomap over MDS is that it preserves local topological relations.

This study uses kernel Isomap. Choi and Choi [1] developed this robust version of Isomap to generalize to new data points, by projecting test data onto the lower dimensionality embedding by geodesic kernel mapping. In addition to this generalization ability, which is based on kernel PCA, kernel Isomap removes outliers to improve topological stability.

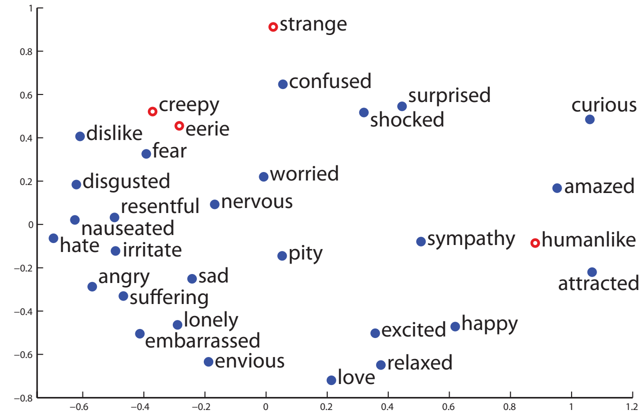

Figure 2: Multidimensional scaling of 31 terms used in participants' ratings of 18 video clips, which include 27 emotions (blue dots) and eerie, creepy, strange, and humanlike (red dots).

3. RESULTS

For both simple regression and the GLM, 2,574 observations (143 participants × 18 video clips) of 27 emotion-related predictor variables were analyzed.

3.1 Multiple Linear Regression

The 27 emotions provided 62% of the information required to predict ratings for eerie ($R^2 = 0.62$, $F = 154.33$, $p = .000$, error var.$= 1.09$). However, just five emotions provided 60% of the information required to predict ratings for eerie ($R^2 = 0.60$, $F = 758.48$, $p = .000$, error var.$= 1.15$). The five emotion terms were disgusted, nervous, dislike, and shocked. The regression hyperplane is

$$\text{eerie} = 0.43\,\text{fear} + 0.18\,\text{disgusted} + 0.17\,\text{nervous} + 0.15\,\text{dislike} + 0.13\,\text{shocked} - 0.15$$

The 27 emotions also provided 62% of the information required to predict ratings for creepy ($R^2 = 0.62$, $F = 156.58$, $p = .000$, error var.$= 1.09$), and just five emotions provided 61% of the information required to predict ratings for creepy ($R^2 = 0.61$, $F = 795.63$, $p = .000$, error val.$= 1.14$). The five emotion terms were fear, disgusted, shocked, nervous, and negative happy. The regression hyperplane is

$$\text{creepy} = 0.46\,\text{fear} + 0.21\,\text{disgusted} + 0.15\,\text{shocked} + 0.14\,\text{nervous} - 0.14\,\text{happy} + 0.70$$

In both cases, fear is strongly predictive of eerie and creepy as are disgusted, nervous, and shocked. All four terms are significant.

The 27 emotions provided only 42% of the information required to predict ratings for strange ($R^2 = 0.42$, $F = 66.95$, $p = .000$, error var.$= 2.02$), and the five most predictive emotions provided 37% of the information to predict ratings of strange ($R^2 = 0.37$, $F = 301.98$, $p = .000$, error var.$= 2.15$). The five emotion terms were confused, negative love, fear, dislike, and disgusted. Confused is most predictive of strange, which may be related to novelty processing.

The higher R^2 for eerie and creepy than strange suggests that eerie and creepy may be more deeply rooted in emotion

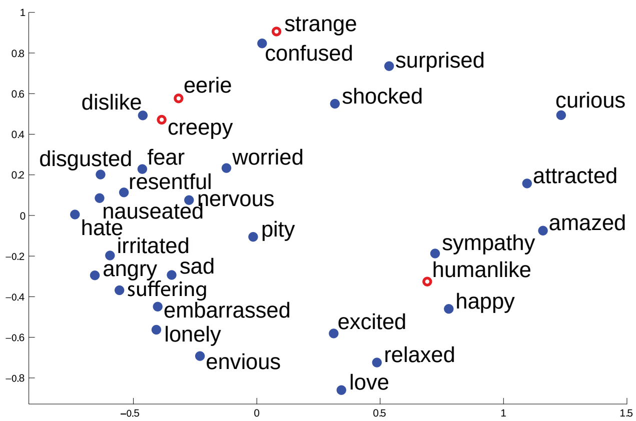

Figure 3: Kernel isometric mapping of 31 terms, which include 27 emotions (blue dots) and eerie, creepy, strange, and humanlike (red dots). Local topological relations were better preserved than with MDS.

and perception, while strange may be more cognitive. These findings for eerie and creepy are compatible with the view that emotions are both perceptions of internal changes (bodily sensations) and of changes in external circumstances, such as danger or loss [13].

3.2 General Linear Model

Ratings of the nonhumanoid robot (Robot 1) were used as a baseline for constructing eight regression models. Amazed, confused, surprised, curious, angry, envious, hate, resentful, nauseated, embarrassed, sad, loneliness, pity, sympathy, attracted, love, and excited were removed because they were redundant, not significant ($p > .05$), or had a high correlation with another variable ($R > .60$). For eerie, creepy, strange, and humanlike, the first model (E1, C1, S1, H1) addresses the impact of emotion, controlling for age and gender, and the second model (E2, C2, S2, H2) includes these demographic factors but also shows the relation between emotion and features of the robots and video clips.

Table 1 shows the results of GLM analysis. In the eerie model, fear is a very strong and significant predictor of eeriness ($\beta = .36$), and shocked ($\beta = .13$), disgusted ($\beta = .12$), nervous ($\beta = .12$), and dislike ($\beta = .09$) are also significant. The second equation, which included dummy variables to account for features of the robots and the video clips, tested whether robot type was linked to eeriness. Only head shot (as opposed to body shot) was significant, but the R^2 did not increase. Although head shots appear to increase eerie and creepy ratings, there is a lack of stimulus control in this survey. So although the results would seem to indicate that such emotions as shock, irritation, dislike, and disgust increase when presented with close-ups of an eerie robot's face, a survey using head and body shots of the *same* stimuli is needed to verify this.

In the creepy model, fear is a very strong and significant predictor of creepiness ($\beta = .41$), and shocked ($\beta = .15$), disgusted ($\beta = .14$), and nervous ($\beta = .11$) are also significant. As with the eerie model, women are more sensitive to creepiness than men. Both head shots and body shots are significant; however, the R^2 does not increase much.

In the strange model, disliked ($\beta = .18$), shocked ($\beta = .16$), disgusted ($\beta = .14$), and fear ($\beta = .12$) are significant to the perception of strangeness. Whether a close-up of the robot's face is shown is significant; however, the regression result shows that the features of the robot and video do not increase the predictive accuracy for strangeness, because the R^2 decreases when it is included in the model.

In the human likeness model, high levels of the emotions shocked ($\beta = .14$), worried ($\beta = .11$), and relaxed ($\beta = .08$) predict high human likeness as well as negative values for dislike ($\beta = -.13$) and fear ($\beta = -.08$). As with the strange model, older participants rated robots as more humanlike than younger participants, showing less sensitivity to their defects.

Mechanical features are defined as Robot 2, 3, and 6; *human features* as Robot 17; and *head shot* as Robot 4, 5, and 7–16. Human features ($\beta = .52$) and head shot ($\beta = .78$) strongly predict the attribution of human likeness to the robot. The reason mechanical features ($\beta = .29$) has a positive correlation is because the nonhumanoid, mobile robot (Robot 1) was used as the baseline.

These results suggest that android designers should consider issues surrounding body image, and especially facial performance. Taken together they dramatically influence people's impression of the robot.

3.3 Factor Analysis

The percentage of variance explained was calculated by factor analysis, applying the maximum likelihood method and Varimax rotation (Table 2). The first two factors explain 28.90% and 14.04% of the variance, respectively, and the third and fourth explain only 4.88% and 2.50% of the variance. According to the factor loadings, hate, nauseated, resentful, disgusted, irritated, dislike, angry, and fear formed the first factor (Table 3). Happy, excited, relaxed, love, amazed, attracted, sympathy, curious, and envious formed the second factor, and were clearly differentiated from the first factor. Sad, suffering, loneliness, pity, worried, nervous, and embarrassed formed the third factor. Shocked, surprised, and confused formed the fourth factor.

Surprisingly, sympathy and pity—two apparently similar emotions that are often grouped together in the literature—belonged to different factors. Sympathy was grouped with happy, excited, relaxed, love, and other positive emotions, but pity was grouped with sad, suffering, loneliness, worried and embarrassed. It was also interesting that excited and relaxed belonged to the same factor and that envy would be found among the positive emotions. Perhaps the woman and the most humanlike robots were viewed positively compared to the odder looking robots that combined the features of human beings and machines.

3.4 Robots with Extremal Ratings

On the seven-point scale ranging from strongly disagree (3) to strongly agree (3), Robot 1, the least human-looking robot, was rated highest for relaxed ($M = 0.27$), after the human. Robot 1 was rated the lowest for for confused (-1.04, tied with the human), shocked (-0.83), surprised (-0.52), embarrassed (-1.89), sad (-1.94), nervous (-1.70), and human likeness (-2.13). Not including the human, Robot 1 was rated lowest for irritated (-1.90), angry (-1.88), dislike

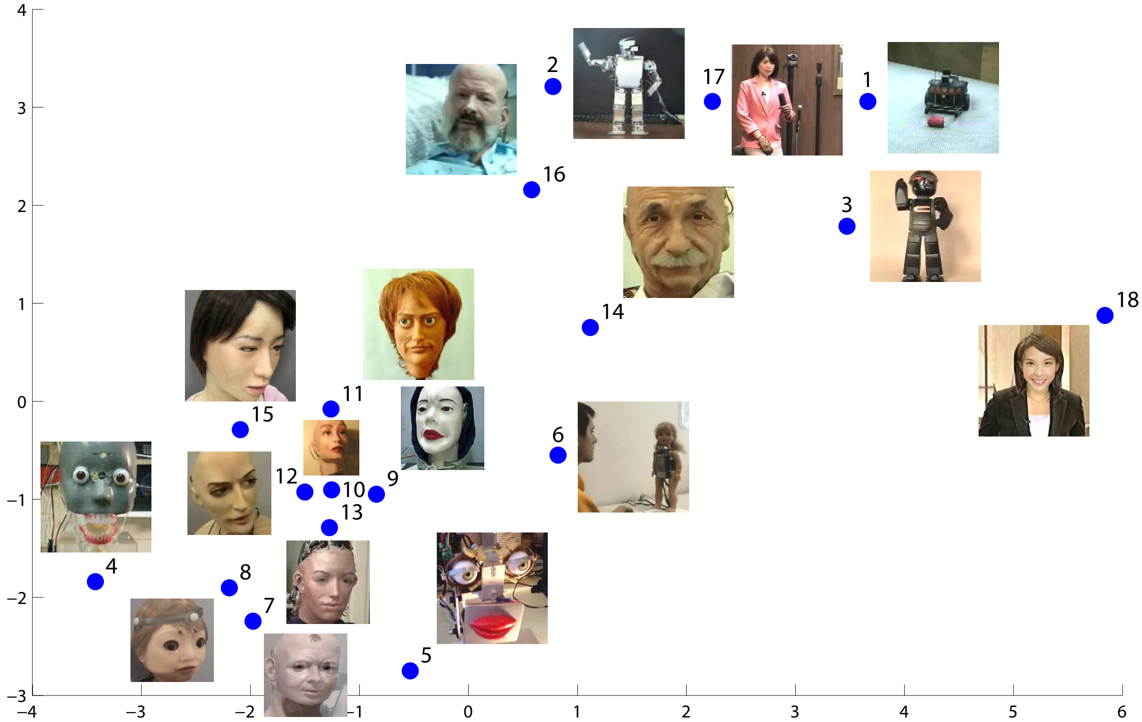

Figure 4: Multidimensional scaling of participant ratings of 18 video clips, which include 17 of robots and 1 of a woman.

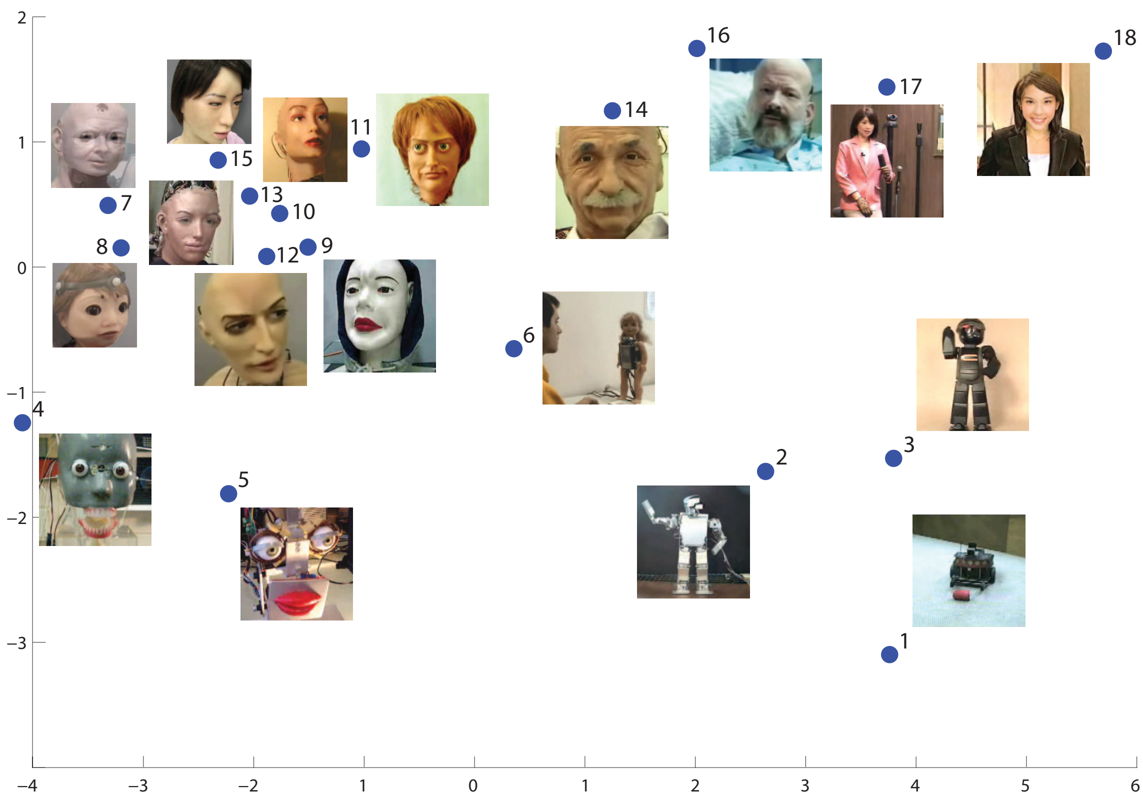

Figure 5: Kernel isometric mapping of 18 video clips. Robots with similar features are more closely grouped than with MDS.

(−1.71), hate (−2.04), resentful (−1.87), disgusted (−2.00), nauseated (−1.94), suffering (−1.90), pity (-1.52), worried (−1.41), eerie (−1.91), and creepy (−2.02).

Robot 3 was rated the highest for attracted (1.81), excited (.34), and happy (.99), after the human. Robot 3 was rated the lowest for fear (−1.91) after the human.

Robot 4, which shows human-looking eyes and teeth but no skin, was rated highest for angry (−1.27), dislike (0.03), hate (−0.64), resentful (−0.68), disgusted (−0.08), nauseated (−0.46), fear (−0.05), eerie (0.19), creepy (0.41), and strange (1.34). It was rated lowest for envious (−1.89), love (−1.51), excited (−1.30), and happy (−1.17). Robot 7, which is an oscillating morph between android and robotic appearance, was rated highest for confused (0.62), shocked (0.42), and surprised (0.52) and lowest for relaxed (−1.51).

Robot 16 was rated highest for humanlike (2.16) among the robots. (The human was rated 2.44, and Robot 17, the second highest-rated robot, was rated 1.95.) Robot 17 was rated highest for amazed (1.71) and curious (1.93) and, after the human for envious (−1.14), sympathy (0.13), and love (0.04).

The human rated highest for envious (−0.78), sympathy (0.35), attractive (1.88), love (0.68), excited (0.52), happy (1.20), relaxed (0.70), and humanlike (2.44). The human rated lowest for irritated (−2.04), angry (−2.04), dislike (−2.02), hate (−2.12), resentful (−2.05), disgusted (−2.29), nauseated (−2.11), sad (−1.92), suffering (−1.95), worried (−1.46), fear (−2.07), pity (−1.54), eerie (−2.04), creepy (−2.18), and strange (−1.92), and tied with Robot 1 for confused (−1.04).

3.5 MDS and Kernel Isomap Comparison

Dislike, disgusted, fear, resentful, hate, irritated and other negative emotions appear near to each other in the MDS visualization (Fig. 2). Eeriness and creepiness were near fear, disliked, disgusted, worried, and confused. Attracted, amazed, sympathy, happy, and curious were concentrated on the side of the figure opposite the negative emotions. In addition, humanlike was located among the positive emotions. However, one should not read too much into this given that there was only one video of a human being.

Figure 3 shows the Isomap visualization of the 27 emotion and 4 other terms (neighborhood size $K = 8$). By better preserving local topological relations, Isomap is more informative than MDS. The somewhat circular placement of the emotions shows the continuity of emotions and bears similarity to some theoretical constructs in psychology. In the geometrical solution of Isomap, creepy and dislike appear closer together than in MDS, as do strange and confused. Humanlike appears much closer to happy and sympathy.

In the MDS visualization of the video clips of the 17 robots and 1 human (Fig. 4), most of the close-up shots were grouped together in the lower, left quadrant. The real woman was far from the other figures. This shows that the participants' emotion-related ratings of the robots place robots nearer to each other, if the face was emphasized or the whole body. However, the proximity of Robot 17, which looks human, to Robot 1, 2, and 3, which look mechanical, made no sense. The problem is that MDS is positioning the robots according to their pairwise distances in the higher dimensional space without regard to local topological relations.

The Isomap visualization of the video clips is similar to the MDS visualization, but the groupings were tighter and more obvious (Fig. 5). The close-up views of robots were nearer to each other. The mechanical-looking robots were clearly grouped, with Robot 1 in the lower right. The three most human-looking robots were close to the real woman, who was in the upper right. Robot 4, the most eerie robot, was in the lower left, and Robot 7, the most ambiguous robot with high ratings of confused, shocked, and surprised, was in the upper left. These groupings make sense.

4. CONCLUSION

A surprising result of this study is that ratings of active robots can reflect relations among human emotions posited by existing theories. For example, we can compare emotions forming a circular pattern in Fig. 3 with similar emotions that Russell [17] places along a circumplex. Fig. 3 lists surprised, happy, relaxed, sad, irritated, fear, and shocked as forming a circular pattern while Russell lists synonymous emotions: astonished, happy, calm, sad, annoyed, afraid, and alarmed. In both the figure and Russell's model, happy–sad and relaxed–fear form opponent pairs of emotions. In addition, Russell's circumplex lists negative emotions on the left and positive emotions on the right, and the same is true in Fig. 3. Higher arousal emotions tend to appear higher in Fig. 3, which roughly mirrors the organization of Russell's circumplex. However, Fig. 3 does not fit Plutchik's model [12] well.

From the standpoint of research on the uncanny valley, the term *fear* is highly predictive of attributions of eerie or creepy to the robot, and disgust, shock, and nervousness are also significant predictors (RQ1). Confusion appeared in attributions of strange, but the lower R^2 suggested that these attributions may be more cognitive than perceptual/emotional (RQ2). Their larger effect sizes and higher R^2 suggest that eerie and creepy may better characterize the uncanny valley than strange (RQ3). Thus, the results cannot rule out the view that the uncanny valley is associated with the fear of one's own mortality *and* with disgust as an evolved mechanism for pathogen avoidance, or a number of other plausible explanations. Indeed, they suggest that the uncanny valley may not be a single phenomenon to be explained by a single theory but rather a nexus of phenomena with disparate causes. Future research needs to clarify more precisely what aspects of a robot's appearance, motion quality, and contingent interaction contribute to the feeling that the robot is uncanny.

Gender and age have only a slight effect on eeriness, creepiness, strangeness, and human likeness ratings of active robots (RQ4). Women were a little more sensitive to eeriness than men, and older people were more willing to overlook defects in a robot by giving it a higher rating for humanlike.

Appearance and motion quality strongly influence how people feel about robots, especially in head shots (RQ5). The experiments of Reeves and Nass indicate that an object's larger size in a close up will make it seem more likeable, memorable, and arousing [15]. They point out, "The human brain did not evolve in a world where images could be made arbitrarily large or small.... If an object, especially one that moved, appeared large, it *was* large or close" (p. 195). However, Reeves and Nass did not experiment with potentially uncanny objects like human simulacra. For these objects, the close-up shot may prove to be a double-edged sword that could increase *or* decrease its likeability or eeriness, depending on many other factors.

What may be unsettling about a robot is not that its overall degree of human likeness places it in an "uncanny valley" but rather that there is a mismatch among elements—some aspects of its form, motion quality, or interactivity may seem more human than others—and it is this we find disturbing. An example of this would be the humanlike eyes and teeth of Robot 4 combined with its absence of skin or hair and the mechanical jerkiness of its movement.

Android designers need to be sensitive to many details concerning the appearance of a human-looking robot and especially the performance of its facial aspects. This will have a big impact on the overall impression the android makes. Those emotions that lie between the two major groups of positive and negative emotions, such as confusion, shock, worry, pity, and love, could be instrumental in determining whether people accept or reject the android.

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