***This is a final draft version of the accepted manuscript. To appear in the International Journal of Social Robotics (2014), http://dx.doi.org/10.1007/s12369-014-0237-z***

# Deriving Minimal Features for Human-like Facial Expressions in Robotic Faces

Casey C. Bennett[1,2] and Selma Šabanović[1]

[1]*School of Informatics and Computing*
*Indiana University*
*901 E. 10th. St.*
*Bloomington, IN, USA 47408*

[2]*Department of Informatics*
*Centerstone Research Institute*
*44 Vantage Way*
*Suite 280*
*Nashville, TN, USA 37228*

Corresponding Author:
*Casey Bennett*
*Department of Informatics*
*Centerstone Research Institute*
*365 South Park Ridge Road*
*Bloomington, IN 47401*
1.812.355.6382
cabennet@indiana.edu

**Abstract**

This study explores deriving minimal features for a robotic face to convey information (via facial expressions) that people can perceive and understand. Recent research in computer vision has shown that a small number of moving points/lines can be used to capture the majority of information (~95%) in human facial expressions. Here, we apply such findings to a minimalist robot face design, which was run through a series of experiments with human subjects (n=75) exploring the effect of various factors, including added neck motion and degree of expression. Facial expression identification rates were similar to more complex robots. In addition, added neck motion significantly improved facial expression identification rates to 100% for all expressions (except Fear). The Negative Attitudes towards Robots (NARS) and Godspeed scales were also collected to examine user perceptions, e.g. perceived animacy and intelligence. The project aims to answer a number of fundamental questions about robotic face design, as well as to develop inexpensive and replicable robotic faces for experimental purposes.

**Keywords**: *Human-Robot Interaction; Facial Expression; Emotion; Minimalist Design; Robot Design*

## 1. Introduction

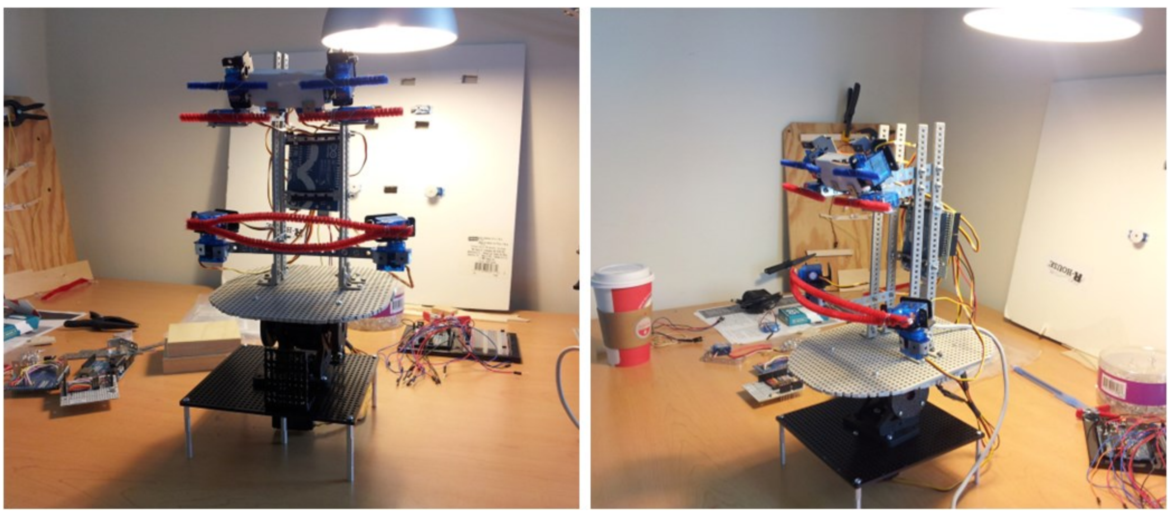
### 1.1 Background/Motivation

This paper explores the facial expression of emotion through a series of studies at the intersection of three fields – computer vision, psychology, and social robotics. Extensive psychological research has shown the universality of certain human facial expressions [1], while recent computer vision research suggests that a small number of moving points/lines can be used to capture the majority of information in human facial expressions. This latter insight has been leveraged to develop automated techniques allowing computers to classify human facial expressions with high degrees of accuracy (~95%) for the six basic Ekman emotions: Happy, Sad, Angry, Fear/Worry, Surprise, and Disgust (see Section 2.1.1) [2,3]. In combination, these previous studies suggest that humans may rely on sparse but specific cues to recognize the emotions of others. Inspired by these approaches, we present four experimental studies that seek to "flip" this finding in order to answer questions about human perception and robot design. Can a small number of moving lines in the face of a robot be used to communicate robotic facial expressions to humans in an understandable way? What factors may affect such perception?

This work has implications for the development of interactive robots – such as those used for companionship, collaboration, and therapeutic or assistive purposes – that need not only detect human facial expressions but also express them. While more complex robots designed to capture facial aspects of nonverbal communication such as Kismet [4] or Eddie [5] already exist, we explore whether simpler facial representations focused on two linear features (upper and lower) and their critical points may be able to convey most of the same information. Other aspects of the face could perhaps be omitted or left as purely aesthetic (and/or economic) choices. This minimalist approach could immensely reduce the complexity of constructing affective robots, or other artificial entities such as digital avatars, allowing for greater flexibility in robot design by freeing up constraints associated with mimicking non-critical aspects of human anatomy, as well as reducing costs. It also holds potential synergy for rapid prototyping in conjunction with new 3D printing techniques (see Sections 2.1.2 and 4.3). Furthermore, such an approach raises interesting cognitive research questions about people's ability to make inferences using incomplete information during social interaction. This research direction contributes to the existing agenda of studying the minimal set of cues that evoke social interpretations and responses from human interaction partners (e.g. Okada's Muu [6] and Kozima's Keepon [7]).

Here we describe the development and results from initial research with such a minimalist robotic face – Minimalist Robot for Affective Expressions (MiRAE) – a robot platform we developed capable of performing an array of facial expressions and neck motions (Figure 1). MiRAE was designed to use easily accessible components (e.g. Arduino microcontrollers; see Section 2.1.2) and requires less than a day of construction time (~6 hours). The project aims to answer a number of fundamental questions about robotic face design, as well as to develop inexpensive and replicable robotic faces for experimental purposes. Our approach also addresses challenges with previous research projects in this area, such as the inclusion of unnecessary confounding variables (e.g. adding ears) or use of custom-made components that limit experimental replicability in the design of robotic faces. The broader goal of this approach is to create a well-documented research platform that can serve as both a material and empirical contribution to the science of human-robot interaction (HRI), robot design, and cognitive research.

**Figure 1: MiRAE**

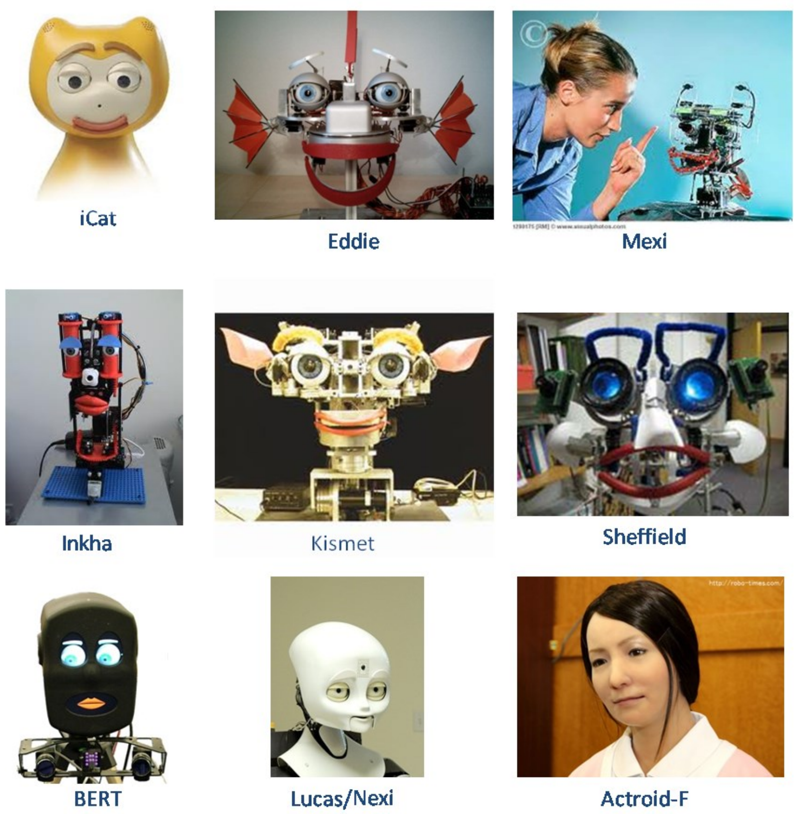


**<u>1.2 Robot Face Overview</u>**

There have been numerous attempts at designing robotic faces over the last thirty years. Many early attempts (pre-2000) are thoroughly reviewed by Fong et al. [8]. We describe various research efforts since 2000 below. These include a wide range of designs, from humanoid faces to animalistic faces to pure iconic/abstract faces. It has been argued elsewhere that iconic/abstract faces are easier to identify with for a broader range of people [9], but that they may not elicit the same visceral response as more humanoid robots [10]. However, challenges also exist with humanoid robotic faces that seek near-replication of human facial features and affect. Their close resemblance to human faces engenders certain expectations in human observers that – when such robotic faces fail to achieve complete human-like behavior – triggers a strong negative response, a.k.a. the infamous “uncanny valley” [9,11,12]. More broadly, there have been a few recent attempts to identify critical dimensions for robotic face design, though these relied largely on meta-reviews of existing robots rather than empirical research [9,13], in contrast to the work described here.

Several advances have occurred in robotic face design in the last dozen or so years (Figure 2) both in terms of physical and computational design, largely based on the basic Ekman emotions and the Facial Action Coding System (see Section 2.1.1). A number of these newer robotic faces also underwent some degree of rigorous experimental testing. One example is Kismet, a fully embodied robotic face developed by Breazeal at MIT [4]. Kismet featured not only a sophisticated design capable of an array of facial motions, but also a complex artificial emotion system (see Section 1.3) that enabled seemingly naturalistic interaction with its environment (including humans) based on its emotional response to environmental stimuli. Eddie, developed by Sosnowski et al. [5], is also capable of an array of facial motions similar to Kismet, and has been additionally evaluated using mechanisms to mimic facial expressions of human observers [14]. BERT2 is a hybrid humanoid face mixing embodied and digital aspects [15]. Feelix, developed by Canamero and Fredslund, was a robotic face designed from Lego Mindstorms™ [16]. Both BERT2 and Feelix implemented similar, though less complex, artificial emotion mechanisms like Kismet.

**Figure 2: Examples of Robotic Faces**




See text (Section 1.2) for appropriate citations.

In discussing the results of our experimentation with MiRAE, we focus on the four robotic faces mentioned above because: 1) they are primarily humanoid, and 2) they underwent some degree of rigorous experimental evaluation similar to that described for MiRAE here (see Section 2.2). However, many other robotic faces have been designed during the same time frame. These include the elephant-like Probo [17], Kaspar [9], the retro-projected faces of Delaunay et al. [18], Sparky [19], the androids Actroid-F [20] and Geminoid-F [21], iCat [22], ROMAN [23], the teddy-bear-like EmotiRob [24], the Sheffield robot [25], Mexi [26], and Lucas/Nexi [27]. This list highlights the range of robotic faces being developed and researched in recent years; it is, however, by no means exhaustive.

Additionally to understand robotic face research in the context of human-robot interaction, it is important to be cognizant of the distinction between the *capabilities* of a given robotic face to make certain facial expressions (e.g. the six basic Ekman emotions) and *applications* of such capabilities to actual interaction. In our view, facial expression capabilities (#1) and their use in human-robot interaction (#2) represent two distinct, though closely related, research questions. In the first question, we are interested in understanding the principles required for robotic faces to create facial expressions that people can perceive/understand, including identifying the minimal features and understanding the effects of facial components, design aesthetics, degree of motion, etc. For the second question, we are interested in the application of facial expression capabilities to simulate/study specific social interaction scenarios and/or behavior. The focus of this latter research agenda is more broadly on the interaction itself, in which facial expressions represent only one component subsumed in the broader system. The second question also often comprises the use of computational models of artificial emotion (e.g. Kismet). Moreover, not all the aforementioned robotic face studies address the second question. We detail robot/agent emotions below (Section 1.3). In this paper, we focus on the first question.

### 1.3 Robot/Agent Emotions

Emotions, as well as non-verbal communication of such emotions, serve a critical role in biological organisms [28,29]. Emotions can form part of the basis for:

1) **Attentional Control** – what features are important to pay attention to in the environment (should I look at that leopard or the rock?)
2) **Reflexive Behavioral Tendencies** – reflex behaviors in emergency situations (it’s a leopard, don’t think, run away!)
3) **Social Interaction/Communication** – critical adaptive behavior in social species (there’s a leopard behind you, hence the fear in my face)

Emotions may also play a role in decision-making, memory, somato-sensory responses, and other cognitive processes [28,30-32]. There is strong evidence for the adaptive role that emotions may have played in the course of evolution, both in humans and other animals [28,29].

Artificial emotions (and/or more broadly affective computing) refer to the ability of technology (computers, robots, artificial agents, etc.) to both recognize and express emotions, typically through the use of computational models [33]. Artificial emotions have been proposed as a potential "cognitive control architecture" in multi-agent systems [28, 34]. For instance, Gadanho and Hallam used artificial emotions as a "filter" between perceptions and actions in order to synthesize appropriate behaviors from noisy perceptual information [28]. Numerous computational models for artificial emotion have also been implemented in robotic face platforms, most notably in Kismet [4], but also in others like Probo [17] and the Roboceptionist [35]. Implementations vary conceptually across robotic platforms, but generally utilize some mathematical formulation to convert perceptions into emotions, facial expressions, and/or behaviors. For instance, the architecture deployed in Kismet utilized four "cognitive" stages – perception, cognitive appraisal, emotional activation, and behavioral (i.e. facial expression/posture) activation – which capture Russell's affect space (see Section 2.1.1) as three mathematical values (arousal, valence, and stance) that can be calculated and communicated across the cognitive process [4]. The end result is a set of numerical values that trigger an emotional response (and related behavior/facial expression) when appropriate (i.e. when some threshold is exceeded).

These computational models, both in robots and multi-agent systems, also enable the use of emotions to address the problem of action selection/switching, which is the challenge in an agent or organism of determining when to continue a current behavior or switch to a new one [36]. Computational models allow the conceptualization of artificial emotions as *trajectories* that bias behavioral tendencies, with thresholds representing the equivalent of attractor basins from a dynamical systems theory perspective. Various time scales of operation for these biases can also be conceived of as constructs reflecting the differences between short-term emotions and long-term moods/drives [1,28,36].

In short, emotions play a critical role in biological organisms, and artificial emotions hold promise to play a similarly critical role in artificial entities. They can potentially create naturalistic social behavior between robots and humans through relatively simplistic mechanisms (along with addressing other problems, e.g. cognitive control, action switching, etc.). However, in order to achieve such social interaction, it is necessary to address the research problem of robotic face design and facial expressions in a systematic way, so as to understand the fundamental features needed to convey information (including artificial emotions) to humans in a way they can perceive and understand. This could be accelerated via inexpensive and replicable robotic platforms and the application of rigorous experimental evaluation (see Section 1.1).

## 1.4 Potential Applications of Minimalist Robotic Facial Expressions

As noted in Section 1.1, this work has implications for the development of socially interactive robots – such as those used for therapeutic or assistive purposes – that need not only detect human facial expressions but also express them. The role of *social intelligence* (including things like artificial emotion and facial expressions) has elsewhere been argued to be a critical component for development of socially interactive robots and artificial intelligence in general [37]. Although many of the aforementioned robots (Section 1.2) have been primarily focused on understanding facial-expression-based human-robot interaction in lab settings, the overarching goal is to apply the findings of such research to robots interacting with people in real-world settings and/or for practical purposes.

Examples of applications of robots capable of emotional display and used for practical purposes include the Rubi education robot [38], service robots [39], the nurse-bot PEARL [40], museum tour-guide robots [41], patient care robots [42], and socially assistive robotics (SAR) for autism therapy [43]. Emotional expression in these types of robots can help users understand the robot's intentions and state, such as if it is over-stimulated or interested in an object [4]. Emotional cues can also be used to manage the behavior of human interaction partners to fit the robot's needs. For example a museum guide robot's angry expression can cue people blocking its path to move out its way so that it can continue guiding them [44].

However, many of these examples currently utilize only limited facial cues and/or expressions, and the design of the emotional expression capabilities is not based on rigorous empirical testing of the underlying principles. The approach utilized here can contribute to the future design of socially interactive robots by providing a minimum set of necessary components that such robots must include and on which they can build further. For example, the case of robots used for autism treatment, the minimal set of cues could be used as a baseline from which individuals can be taught to interpret more complex emotional expressions [45]. Furthermore, a simple minimalist robotic platform can serve as the basis for studying human cognition, including social cognition, as has been argued previously – this, however, necessitates certain capabilities (see Section 4.2)

# 2. Methods

## 2.1 Robot Face Design

### 2.1.1 Design Overview

The robotic face design utilized here was inspired by recent research in computer vision on human facial expressions and based on Ekman's theories of emotion and the Facial Action Coding System (FACS) [1]. According to this theory, there is a set of six basic emotions - Happy, Sad, Angry, Fear/Worry, Surprise, and Disgust – which are rooted in evolution and displayed using similar features across human cultures (Figure 3). These features are referred to as *Action Units* (AUs, 44 in total), which capture all possible movement of the muscles of the human face. Activation values for these AUs can be calculated and used to accurately identify the emotion expressed in a given human face, regardless of the idiosyncrasies of the individual face [1,46]. Given that the ability of people to recognize these facial expressions appears to be instinctive, it can be reasoned that humans may use these same AU features to recognize emotions in facial expressions of other people [29,47]. There is evidence, however, that the display and reading of facial expressions may be variable across cultures [48-50], posing further questions for investigation (see Section 4.3).

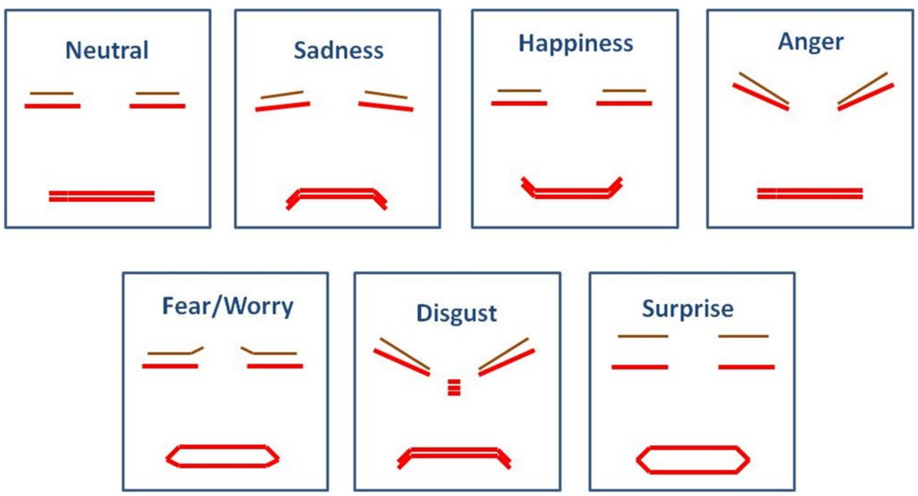
**Figure 3: Human facial expressions of six basic Ekman emotions**

In order (left-to-right, top-to-bottom) – Disgust, Happiness, Sadness, Anger, Fear and Surprise [2].

Of note, there is debate as to how to conceptualize these emotions, primarily between Ekman's categorical view [1] and Russell's three-dimensional *affect space* view (a.k.a. the circumplex model) [51]. In short, Russell's model utilizes three continuous-valued dimensions (arousal, valence, and stance) and treats all "emotions" as manifestations in the resulting 3D *affect space*. In other words, what we classify as emotions (and/or emotional facial expressions) are in actuality ill-defined points in continuous space, rather than distinct categories [52]. This view contrasts with the basic Ekman categorical emotions (described above). However, this debate has been repeatedly detailed in the literature [2,4,5,15,17], and primarily centers on what emotions constitute (not whether they exist). As such, we will not address it here.

Feature selection techniques from machine learning have revealed that a small number of moving points/lines (i.e. a subset of 8-10 AUs) can be used to capture the vast majority of information in human facial expressions (~95%). This insight had been leveraged over the past several years in the computer vision community to develop automated techniques for classifying human facial expressions via computers [2,3,53]. These were translated into the schematic representation shown in Figure 4, comprising two principle linear feature sets: upper (eye/brow) and lower (mouth). Similar sparse cues have also been indicated to play a role in human perception of emotion [54].

**Figure 4: Schematic Facial Expressions**




These simple schematic representations were used as the basis for the embodied robotic face design (Section 2.1.2) as well as the digital avatar version (Section 2.1.4) below. The goal of the experiments was to start with a simple, minimalist robotic face with as little complexity as possible, perform thorough scientific experimentation of its facial expression capabilities with human users, and then build from that. For instance, if one degree-of-freedom (DOF) for eye motion turned out to be insufficient for a given task, then additional DOFs could be added. If simple lines proved insufficient, then more robust shapes could be evaluated. In short, we wanted to minimize our *a priori* assumptions about what was and was not important. We also wanted the embodied robotic face to be as similar to the digital avatar version for experimental purposes (Experiment #1, see Section 2.2).

Although many other researchers have utilized similar approaches in the design of robotic faces [4,5,55], our approach differs in its strict adherence to the minimal features (AUs) without addition of extraneous (and/or potentially confounding) attributes, e.g. ears or other aesthetic properties, as well as in the iterative process of designing and evaluating these features.

### 2.1.2 Embodied Face Design

The embodied face (MiRAE) was constructed using inexpensive, easily accessible components in keeping with a minimalist design approach (see Figure 1 above). Principally, physical construction was accomplished using universal metal joints, plastic arms, and universal plates from Tamiya (http://www.tamiyausa.com); 10 sub-micro Hitec servos (http://www.hitecrcd.com); and various servo brackets. Arduino Uno v1.1 microcontrollers (http://www.arduino.cc) were used to create and control functionality of the robotic face. Combinations of servo motors were used to create the needed motion and degrees-of-freedom (DOF): 1 DOF for each eye, 2 DOF for each eyebrow, 2 DOF for the mouth corners/lips, and 2 DOF for the neck. Combined actuation of these simple DOFs could simulate complex motion, such as the parting of lips and bearing of teeth (see Figure 6 below). Facial features such as eyes, eyebrows, and the mouth were simulated using colored pipe cleaners affixed using gauge wire. More explicit instructions are available at the authors' lab website online (http://r-house.soic.indiana.edu/mirae/MiRAE_Construction_Manual.pdf) and the main author's website (http://www.caseybennett.com/Research.html). All the programming code, including the C++ libraries (see below), is also available on those websites. In addition, schematics for completely 3D printing the robot-face and head (as well as modifying it for other purposes) will be available from those websites.

In total (including the neck mechanism described below, Section 2.1.3), the overall cost for the robotic face is approximately $150-175 USD. Total construction time averages roughly 6 hours. The potential exists to enhance the current bare-bones design – such as through the use of 3D printing to create more realistic facial features like eyes. However, the goal here was to minimize aesthetic properties so as to focus on the effect of the features themselves, as well as provide a direct comparison to the digital avatar (see Section 2.1.4).

The programming code to control the robotic face was written in the Arduino language, which is based on C++, as a C++ library (available online, see above). Some extensions to the basic Arduino language were written as structures to handle multi-variable function returns. The code was designed as a three-tiered system. The main program could call functions that specified facial expressions, passing in the *direction* (used to make or undo an expression) and *degree* (continuous value used to determine the strength or degree of the expression – i.e. smaller vs. larger). The facial expression functions would in turn call lower functions that moved specific facial components given a direction and degree – in essence these facial component functions roughly relate to specific AUs in the Facial Action Coding System (FACS). This approach provides several benefits – e.g. it allows for easy extensibility to include new expressions, AUs, or types of facial motion. It also permits a direct linkage between the programming code used to control the robot face and underlying theory about human emotion and facial expression. Also of note, motion (in both the embodied and digital avatar versions) was implemented as *gradated motion*, so that facial expressions occurred over a matter of a few hundred milliseconds (as they would in a real human face), rather than instantaneously. The platform also allows for nuanced control of the expressions and their level of intensity (i.e. degree) in experimental situations.

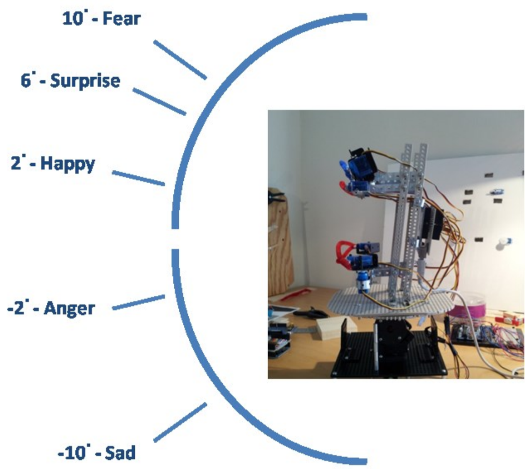
A comparison of the DOF of MiRAE and several other robotic faces designed for human-like facial expressions is provide in Table 3 in the Results section.

### 2.1.3 Added Neck Motion/Neck Posture

An additional question of interest was the effect of added neck motion (or neck posture) on human facial expression identification (FEI) in robotic faces. Previous work has studied neck motion/posture in both embodied and digital robots as it relates to general human-robot interaction and communication [4,56,57], but not specifically related to facial expression identification. In order to address this, a neck mechanism was constructed using a ServoCity SPT200 Heavy-Duty Pan & Tilt System and two Hitec high-torque HS-485HB servos. The "face" of MiRAE was mounted on top of this mechanism, allowing for both vertical (tilt, i.e. up/down) and horizontal (pan, i.e. left/right) rotational motion, similar to a human neck. More explicit details are provided online (http://r-house.soic.indiana.edu/mirae/MiRAE_Construction_Manual.pdf).

The final aspect was determination of how much motion should be applied for the each of the Ekman emotions. Surprisingly, literature on neck motion/posture as it relates to facial expressions is limited, even in humans [58]. As such, we ran preliminary trials (using lab personnel only) *before* the actual experiments described below to arrive at reasonable estimates. We found that a relatively small amount of vertical (i.e. rotational tilt) neck motion created a rather large effect. The utilized values for each emotion (with negative values indicating down and positive indicating up, see Figure 5) were as follows: Happy (2°), Sad (-10°), Anger (-2°), Fear (10°), and Surprise (6°). Disgust neck motion is still yet to-be-determined (see Section 4.2). A video of MiRAE making these facial expressions, plus the neck motion, is available online (http://r-house.soic.indiana.edu/mirae/MiRAE_neck_video.mpg).

**Figure 5: Added Neck Motion**




Note: Angle representations in figure are not to scale.

### 2.1.4 Digital Avatar

A digital avatar version was implemented for the first experiment (Section 2.2) so as to compare the minimal features in an embodied vs. digital form. The digital avatar version was designed to look virtually identical to the schematic representations (Figure 4), and thus by extension as similar to the embodied version as possible. It was implemented using Python 2.7 (www.python.org) and the TkInter toolkit package (http://wiki.python.org/moin/TkInter). Programming was implemented using the same approach as for the embodied face (e.g. three-tiered design, gradated motion) as described above (Section 2.1.2).

## 2.2 Experimental Design

We conducted a series of four experiments to evaluate human abilities to perceive and understand robotic non-verbal affective cues while varying factors related to robot and study design. The four experiments included evaluations of:

1) Embodied robotic face vs. digital avatar version
2) Effect of additional neck motion (vs. no neck motion)
3) Effect of "priming" subjects using human facial expressions (vs. no priming)
4) Effect of the degree of expressions (smaller vs. larger)

We recruited 75 unique subjects across all experiments (total n=75), 30 for the first experiment and 15 apiece for the other three. Subjects were randomly assigned to experiments, and <u>each subject participated in only one experiment</u>. Importantly, we were concerned about potential effects of repeatedly showing human subjects another entity making facial expressions, the so-called *priming* effect from psychology (we test this in Experiment #3). All subjects were college undergraduates in the United States (i.e. generally 18-23 years old) from various disciplines (e.g. computer science, psychology) and of varying gender (approximately 54.7% female). All the experiments were performed during the same 3 month time period (October 2012 thru January 2013).

In all experiments, subjects observed the robotic face (and/or digital avatar, if applicable) making a randomized pre-set series of facial expressions (the six Ekman emotions, less Disgust; see below) and responded to a three-item Facial Expression Identification (FEI) instrument for each expression. On the FEI, subjects were asked to first identify the expression (Question #1) and to rate the strength of expression (Question #2). The FEI used a similar 7-option forced-choice design for Question #1 as was used in studies with Kismet, Eddie, etc. for comparability purposes (FEI available online in English and Japanese: http://r-house.soic.indiana.edu/mirae/FEI_Instrument.docx) [4,5]. The FEI also asked subjects an additional question (Question #3) for each expression, allowing (but not requiring) them to select one or more "other expressions" they thought the robot might be displaying, if desired. For instance, if the subject selected Surprise as the most likely emotion for a given expression on Question #1, but also thought the expression might have been Fear, they could circle Fear on Question #3. Question #3 was included on the FEI since there has been some criticism of the forced-choice emotion labeling task, going all the way back to Ekman even [59]. In subsequent sections, we refer to *main accuracy* based on the single answer from Question #1, and *other accuracy* when including answers from both Question #1 and #3. *Strength ratings* are based on Question #2. Finally, subjects were administered the Negative Attitudes toward Robots Scale (NARS, prior to each experiment) [60] and Godspeed instruments (after each experiment) [61].

During each experiment, the robotic face (and/or digital avatar, if applicable) made each expression for several seconds, then returned to a neutral face. A pause of 15 seconds was provided between expressions to allow participant to fill out the FEI. Participants simply watched the robot, i.e. there was no interaction. The robot (nor avatar) did not speak or make affective sounds. The robot is capable of actual "interaction", e.g. it can see that people are there and react to them, track them, etc. However, this was <u>not</u> done in any of the experiments reported here.

For Experiment #1, 30 subjects were randomized into two groups: one group seeing the embodied robot version first and the other group seeing the digital avatar version first. Both groups saw both versions (embodied and digital), only the order differed. This was done to rule out any potential effects due to the ordering. <u>For subsequent experiments, the results of this first experiment were considered the "baseline" (i.e. the control).</u>

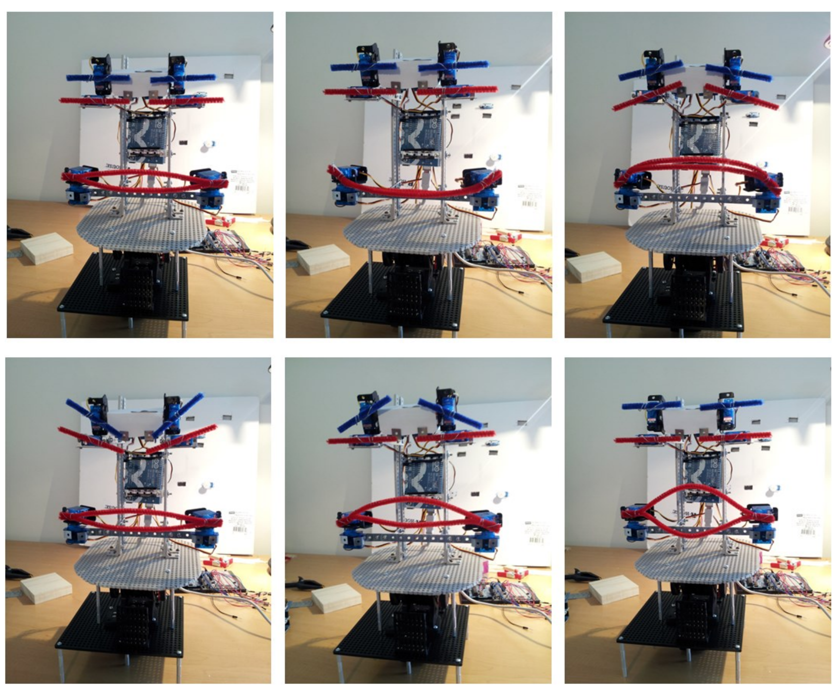
For Experiment #2, 15 subjects observed the embodied robotic face making facial expressions with the addition of the added neck motion described in Section 2.1.3.

For Experiment #3, 15 subjects observed the embodied robotic face making facial expressions *after* being shown a priming stimulus of a human making the six Ekman emotions with each expression labeled (Figure 3 above). Subjects observed a printed copy of the priming stimulus for approximately 30-45 seconds total (i.e. about 5-7 seconds per expression), guided by the experimenter. Nothing was pointed out to subjects regarding details about the facial expressions or specific facial cues.

For Experiment #4, 15 subjects observed the embodied robotic face making facial expressions with roughly half the degree (50%, in numerical terms) of that seen in the first experiment– i.e. subjects in this experiment observed the "smaller" degree (50%), while subjects in the first experiment observed the "larger" degree (100%). Explicit numerical values for the degrees of motion of individual components are provided in the detailed instructions on the authors' website (see Section 2.1.2).

Of note, even though MiRAE has the ability to express Disgust using a similar approach as Kismet or Eddie (i.e. "Lip Twist"), we did not address Disgust in this current research, for reasons discussed in Section 4.2. Figure 6 shows MiRAE's basic display at the apex of the five expressions (without added neck motion) used in all experiments, plus the neutral starting expression.

**Figure 6: MiRAE Display of Emotions**



Expression at apex of motion, without neck motion. In order (left-to-right, top-to-bottom) – Neutral, Happiness, Sadness, Anger, Fear and Surprise.

## **2.3 Analysis Plan**

The analysis plan was conceived *a priori*, and served as the basis for the experimental design detailed above (Section 2.2). Due to time/costs constraints (i.e. limited sample size), we chose to specifically test only four specific hypotheses, rather than all possible hypotheses. Each experiment above was designed to test one of these hypotheses. The study had two main parts: 1) A paired within-subjects design for Experiment 1 only, comparing the accuracy/strength-ratings of the embodied robotic and digital faces, and 2) a between-subjects design re-using the results from Experiment 1 (for the embodied robot) as the baseline (i.e. the control) and comparing each Experiment #2-4 to it to test for effects (listed in Section 2.2).

We thus do not test for all group-comparisons directly, e.g. added neck motion (Experiment #2) vs. reduced degree of expression. Rather, we compare each treatment condition in Experiments 2-4 with the "baseline" (i.e. Experiment #1). Again, this was a consequence of time/costs constraints - the approach was decided upon *a priori*, in order to allow us to take the best advantage of the sample size and power we had available.

Each of the four hypotheses was thus a two-group comparison: either embodied vs. digital (for Experiment #1), or control vs. effect (for Experiments #2-4)). For Experiment 1, this entailed paired $t$-test comparison, and for all other experiments it entailed independent-samples $t$-tests. We also tested for ordering effects (the effect of showing either the embodied or digital face first) in Experiment 1 using an independent-samples $t$-test. Significance was measured at the $p<.05$ level (two-tailed). Effect sizes are reported using Cohen's $d$.

Given sufficient time and money, a larger study with a full fixed-effects ANOVA testing more hypotheses/group-comparisons would be of great interest. However, such an experimental design would require testing at least twice as many hypotheses and a much larger sample size to achieve sufficient statistical power – even our current reduced-hypothesis analysis has only modest statistical power (approximately 0.5, as calculated post-hoc). In practice, this sort of approach is still uncharted territory in many ways as far as robotic face experiments go; as such, this study represents a good preliminary step in that direction.

# **3. Results**

## **3.1 Embodied vs. Digital Results**

Table 1 shows the identification results between the embodied robotic face (MiRAE) and the digital avatar version (Experiment #1), including the accuracy of the main identified emotion and the accuracy when including the "other" identified emotions (see Section 2.2). In general, the results are comparable, though the digital avatar version was slightly higher for most expressions (avg. main accuracy, digital vs. embodied: 88% vs. 84%). The difference was not significant for main accuracy (paired *t*-test: $t(29)=1.44$, $p=.161$), though it was when including other accuracy ($t(29)=2.11$, $p=.043$, effect size=.49). This difference made some intuitive sense, in that it was easier to maintain better fidelity to the FACS in the digital version. However, the perceived strength ratings were on average slightly lower for the digital avatar (but not significant). Also of note, the perceived strength of expression significantly correlated with the identification accuracy ($r^2=.896$ for the embodied version). A confusion matrix of the results is provided in supplementary Table s1.

**Table 1: Main Results of Expression Recognition**

| | Expression | Main Accuracy | Other Accuracy | Strength Rating |
|---|---|---|---|---|
| **Embodied** | Happy | 96.7% | 96.7% | 7.31 |
| | Sad | 100.0% | 100.0% | 8.30 |
| | Anger | 86.7% | 93.3% | 7.25 |
| | Fear | 43.3% | 63.3% | 6.25 |
| | Surprise | 96.7% | 100.0% | 7.96 |
| **Digital** | Happy | 100.0% | 100.0% | 6.93 |
| | Sad | 100.0% | 100.0% | 8.09 |
| | Anger | 100.0% | 100.0% | 7.98 |
| | Fear | 53.3% | 66.7% | 6.38 |
| | Surprise | 86.7% | 100.0% | 7.22 |

Facial expression identification results from Experiment #1 for the Embodied Robot (top) and Digital Avatar (bottom) are shown. For each expression, main accuracy, other accuracy, and average strength ratings from the FEI instrument are provided (definitions for each are provided in Section 2.2).

Table 2 shows the comparison between MiRAE and several other recent robotic faces: Kismet [4], Eddie [5], Feelix [16], BERT [15], and Geminoid-F (Table 5 in [21], Americans only). Generally, MiRAE produced higher, or at least comparable, identification accuracy rates for all expressions, despite its minimalist design and ease/brevity of construction. Across all faces, similar patterns can be observed (e.g. relative dip in Fear identification). Note that many robotic faces from the last decade are not included because similar rigorous experimental evaluation was never performed/reported.

**Table 2: Robot Face Comparison**

| Expression | MiRAE (n=30) | Eddie (n=24) | Kismet (n=17) | Feelix (n=86) | BERT (n=10) | Geminoid (n=71) |
|---|---|---|---|---|---|---|
| Happy | 97% | 58% | 82% | 60% | 99% | 88% |
| Sad | 100% | 58% | 82% | 70% | 100% | 80% |
| Anger | 87% | 54% | 76% | 40% | 64% | 58% |
| Fear | 43% | 42% | 47% | 16% | 44% | 9% |
| Surprise | 97% | 75% | 82% | 37% | 93% | 55% |
| Disgust | - | 58% | 71% | - | 18% | - |
| Average[a] | 85% | 57% | 74% | 45% | 80% | 58% |

Facial expression identification average accuracy for the six Ekman emotions is shown for several robotic faces (including the own used here, MiRAE). The number of subjects (*n*) is shown for each study as well. Appropriate citations for each are provided in text. [a]Averages do not include Disgust, since not all studies included it.

Table 3 provides the degrees-of-freedom (DOF) for different facial features across the same robotic faces in Table 2. In particular, the results suggests that moveable facial features such as eyelids, ears, and animal-like crowns, which were used in some of the previous studies, appear to be dispensable for creating recognizable robotic facial expressions for affect (the Ekman emotions). Comparable recognition rates were obtained in the current study using only movement of the eyes, eyebrows, and mouth. It should also be noted that several of the robots (e.g. Feelix, Geminoid) took advantage of facial symmetry to reduce the DOF listed in Table 3, e.g. using only a single motor to rotate both eyebrows rather than two separate motors, while several (Kismet, Eddie, MiRAE) did not. In the current study, only symmetrical expressions were used, which indicates the DOF of those latter robots could be potentially reduced (by roughly half), at least for the Ekman emotions. Further research would be needed to empirically establish the value, if any, of asymmetrical expression capabilities.

**Table 3: Robot Face DOF Comparison**

| Feature | MiRAE | EDDIE | Kismet | Feelix | Bert | Geminoid |
|---|---|---|---|---|---|---|
| Eyes | 2 | 3 | 3 | - | 2 | 2 |
| Eyelids | - | 4 | 2 | - | 1 | 1 |
| Pupil Size | - | - | - | - | 2 | - |
| Brows | 4 | 4 | 4 | 1 | 4 | 2 |
| Ears | - | 6 | 4 | - | - | - |
| Crown | - | 1 | - | - | - | - |
| Mouth | 4 | 5 | 5 | 3 | 4 | 2 |
| Neck | 2 | - | 3 | - | - | 4 |
| Total | 12 | 23 | 21 | 4 | 13 | 11 |

Degrees-of-Freedom (DOF) are shown for each robotic face. This can be compared facial expression recognition accuracy in Table 2. Dashes indicate that there was no DOF for the given feature for a particular robotic face. Appropriate citations for each are provided in text

Godspeed and NARS values were also analyzed for differences between the embodied robotic face and the digital avatar version. Table 4 shows the values across the five domains of the Godspeed scale. The numbers were comparable across all domains, with only animacy and likeability showing statistically higher values for the embodied version (at the $p<.05$ level, paired $t$-test: $t(29)=2.18$, $p=.037$ and $t(29)=2.36$, $p=.025$, respectively). Analysis of the NARS revealed no significant relationships with either identification accuracy or Godspeed ratings (data not shown).

**Table 4: Embodied vs. Digital – Godspeed Ratings**

| Category | Embodied | Digital | Sig. | Effect Size |
|---|---|---|---|---|
| Anthropomorphism | 2.26 | 2.08 | 0.228 | |
| Animacy | 2.44 | 2.14 | 0.037* | 0.40 |
| Likeability | 3.58 | 3.26 | 0.025* | 0.52 |
| Perceived Intelligence | 2.86 | 2.85 | 0.940 | |
| Perceived Safety | 3.83 | 3.91 | 0.500 | |

Ratings for each of the five Godspeed-scale domains are provided for the Embodied Robot and the Digital Avatar on the left. Significance values ($p$-values) testing for significant differences between the Embodied Robot and the Digital Avatar in each domain – based on paired $t$-tests – are provided on the right. Significance values that are statistically significant are starred and effect sizes are provided.

Also of note, there was no significant difference due to ordering (whether subjects saw the digital or embodied version first) based on overall main identification accuracy (independent samples $t$-test: $t(28)=1.57$, $p=.127$), other accuracy ($t(28)=.866$, $p=.384$) or strength ratings ($t(28)=1.35$, $p=.181$).

## 3.2 Added Neck Motion Results

Table 5 shows the results from the added neck motion (or neck posture, Experiment #2). Identification accuracy values were pushed to 100% for all expressions, except for Fear (n=15). In short, identification accuracy was generally higher for the embodied robotic face with neck motion (Table 5) than without it (Table 1), avg. main accuracy: 87% vs. 84%. Effects were similar to Experiment 1, in that main accuracy differences were not significant, but differences were statistically significant when including other accuracy (independent samples $t$-test: $t(43)=2.50$, $p=.016$, effect size=.72). This also effectively eliminated any difference in identification accuracy between embodied and digital versions as seen in Experiment 1. Strength ratings were significantly increased for all expressions (independent samples $t$-test: $t(43)=2.11$, $p=.042$, effect size=.62), except surprise which remained roughly stable.

**Table 5: Added Neck Motion**

| | Expression | Main Accuracy | Other Accuracy | Strength Rating |
|---|---|---|---|---|
| **Embodied** | Happy | 100.0% | 100.0% | 9.07 |
| | Sad | 100.0% | 100.0% | 8.80 |
| | Anger | 100.0% | 100.0% | 8.00 |
| | Fear | 40.0% | 86.7% | 8.60 |
| | Surprise | 100.0% | 100.0% | 7.80 |

Even for Fear, the "other" accuracy did significantly increase, indicating that subjects generally recognized that the expression could be Fear, even if they were unsure. Interestingly, when Fear was misidentified in Experiment #1 (Section 3.1), it was most often misidentified as Sad (approximately 83% of misidentifications, see supplementary Table s1). In contrast, for Experiment #2, it was most often misidentified as Surprise (approximately 90% of misidentifications). This may suggest confusion due to the neck motion used for Fear and Surprise during Experiment #2, and indicate that alternative neck/body postures for Fear should be explored.

Godspeed and NARS ratings were also collected for the robotic face with added neck motion. However, the data were not significantly different from those reported for the embodied robotic face without neck motion (Table 4) and are omitted for brevity.

## 3.3 Primer Effect Results

A question of interest was the effect of "priming" subjects by showing them images of a human making the same facial expressions prior to observing the robotic face. We hypothesized this may increase the identification accuracy by alerting an individual's cognitive processes to prepare for specific facial cues (either consciously or unconsciously). Importantly, we were concerned about potential effects of repeatedly showing human subjects another entity making facial expressions, the so-called *priming* effect from psychology. The priming effect is notorious in many psychology experiments [62-64], but potentially an unacknowledged source of bias in robotic facial expression experiments.

**Table 6: Primer Results**

| | Expression | Main Accuracy | Other Accuracy | Strength Rating |
|---|---|---|---|---|
| Embodied | Happy | 93.3% | 93.3% | 8.11 |
| | Sad | 100.0% | 100.0% | 8.90 |
| | Anger | 100.0% | 100.0% | 8.10 |
| | Fear | 53.3% | 66.7% | 6.38 |
| | Surprise | 100.0% | 100.0% | 9.03 |

Priming showed mixed results in effects on perceptions of robotic facial expressions. Comparing Table 6 to the embodied results in Table 1, average main accuracy increased to 89% vs. 84%. This followed a similar pattern to that seen with the digital avatar (Experiment #1) and/or added neck motion (Experiment #2). However, this was not statistically significant for either main or other accuracy. Strength ratings, on the other hand, were significantly increased (with the exception of Fear; independent samples *t*-test: $t(43)=2.10$, $p=.042$, effect size=.59). In short, priming mainly affected people's perception of the intensity of the expression, without significantly altering their interpretation of which emotion was being communicated.

In this case, the primer was shown immediately before the robotic face experiment (short-term). It is not clear if this effect is long-term as well. It does raise some possible concerns about repeatedly showing human subjects another entity making facial expressions (either human or robotic). In this study, *we took precautions so as to only use each subject once for a single experiment*, as noted in Section 2.2. However, in other studies where subjects may have possibly been re-used across experiments, reported results could potentially be erroneous due to such an effect. This warrants caution for experimental design in future studies of human-robot interaction and robotic facial expression.

Godspeed and NARS ratings were also collected for the robotic face with primer effects. However, the data were not significantly different from those reported for the embodied robotic face without the primer (Table 4) and are omitted for brevity.

## 3.4 Varying Degrees of Expression Results

Table 7 shows the results when the robotic face made expressions using one-half the degree of motion as in Experiment #1 (i.e. 50% less motion). In short, there were no statistically significant differences for main accuracy, other accuracy, strength ratings, Godspeed, or NARS (e.g. compare Table 7 vs. the embodied results in Table 1). Interestingly, human subjects were generally still able to identify the emotion being expressed with similar accuracy as with the larger degree of motion. Fear and Happy were the only expressions that exhibited any notable decline. In contrast to our hypothesis, there was *not* a consistent reduction in strength rating across emotions when a smaller degree of motion was used – some expressions actually increased slightly.

**Table 7: Smaller Degree of Expression Results**

| | Expression | Main Accuracy | Other Accuracy | Strength Rating |
|---|---|---|---|---|
| **Embodied** | Happy | 80.0% | 80.0% | 6.50 |
| | Sad | 93.3% | 93.3% | 7.42 |
| | Anger | 93.3% | 93.3% | 7.78 |
| | Fear | 20.0% | 46.7% | 6.50 |
| | Surprise | 100.0% | 100.0% | 8.20 |

An open question is where the lower bound lies for motion in robotic facial expressions that people could still perceive and understand. Our hypothesis was that there would be a continuously decreasing identification accuracy rate and strength rating as degree of motion was reduced. However, at least in a comparison of two specific degrees of motion in a minimalist robot, this phenomenon was not consistently observed across expressions.

## 4. Discussion

### 4.1 General Discussion

This study explored deriving minimal features for a robotic face to convey information (via facial expressions) that people can perceive/understand. The robotic face (MiRAE) was run through a series of experiments with human subjects (n=75) exploring the effect of various factors, including added neck motion and degree of expression. Facial expression identification rates were similar to more complex robots. Results suggest that movement of certain facial features (e.g. eyelids, ears, animal-like crowns) is not requisite for creating recognizable facial expressions of affect (Ekman emotions) – movement of the eyes, eyebrows, and mouth alone is sufficient. In addition, added neck motion improved facial expression identification rates to 100% for all expressions (except Fear), as well as significantly increasing perceived strength of expression.

The embodied robotic face was also compared with a digital avatar version. Facial expression identification accuracy was higher for the digital avatar, which was attributed to the fact that it was easier to maintain fidelity with the FACS in the digital version. However, adding neck motion to the embodied robotic face eliminated this difference. On the other hand, perceived strength of expression ratings were slightly lower for the digital version, and Godspeed ratings revealed significantly higher perceptions of animacy and likeability for the embodied robotic face versus the digital avatar, which may make the former more appropriate for socially-interactive and assistive purposes.

Additional findings included that perceived strength of expression correlated strongly with identification accuracy rates. There was also an apparent effect on perceived strength due to "priming" subjects using human facial expression images as stimuli, which may suggest caution in experimental design of robotic face studies. Alternatively, it might also suggest that people could be quickly and explicitly trained to recognize robotic expressions with high accuracy, possibly as an alternative to including additional components, added motion, and/or more sophisticated features. Lastly, we found that human subjects were still able to identify robotic facial expressions even when half the degree of motion was used. An open question exists as to where the lower bound of motion lies for robotic expressions that people can perceive and understand.

### 4.2 Implications/Limitations

As mentioned in Section 1.1, this study has a number of implications for robotic face design. The results shown here hold promise to immensely reduce the complexity of constructing affective robots, allowing for greater flexibility in robotic design for social interaction. It may also free up constraints associated with mimicking non-critical aspects of human anatomy. More broadly, the minimalist approach could be applied to many aspects of robotic form – e.g. previous applications to the study of affective, attentional and rhythmic cues in Keepon [7] and relational interaction in Muu [6] – as well as exploration of embodied cognition of artificial emotions.

The development of inexpensive robotic platforms utilizing widely available materials also holds promise to enhance replicable and methodologically-rigorous experimentation in human-robot interaction – and thus the advancement of "robotic science" – in contrast to robotics as purely an endeavor in engineering. Moreover, such an approach can enhance our understanding of human cognition. MacDorman and Ishiguro suggest that robots can act as unprecedented research tools for the study of social cognition by providing controllable stimuli in experimental and field studies; their behaviors can be carefully controlled, finely tuned and varied, and repeated exactly and indefinitely, which is challenging even for well-trained human confederates [65,66]. Their proposed "android science," however, relies on very complex and expensive platforms that will be difficult to make widely available to the research community. Others have suggested that robots can be used to validate specific models of human embodied cognition, which can be implemented on robotic platforms and tested to see whether the expected human-like behavior is displayed [67,68]. Our suggested minimalist platform makes both of these approaches to the scientific study of human-human and human-robot interaction feasible. We focus particularly on answering cognitive science questions around people's abilities to make inferences using incomplete information during social interaction. Using robots to study human cognition, including social cognition, in lieu of human confederates necessitates robots capable of making signaling cues based on the way humans do. Having a simple minimalist platform containing such capabilities with which to study the various aspects of human affective perception and interaction – but without the cost and complexity – would be a boon to not only robotics, but also psychology and cognitive science.

There are many factors associated with facial expressions, social communication, and the recognition thereof that are not addressed in this study. Some of these are mentioned in Section 4.3. In general, it should be noted that there is much work left to do to evaluate the importance of many aspects of such communication, both in human-to-human and human-robot interaction. This study only represents a small slice of the numerous questions that could be asked.

Additionally, the study did not consider the emotion of Disgust. MiRAE is capable of making this facial expression using the same approach as Kismet [4] and Eddie [5]. This approach entails the use of what we refer to as a "Lip Twist" expression, which involves the twisting of the lips so that one mouth corner is raise and the other lowered while simultaneously cocking the eyebrows in some fashion. However, this "Lip Twist" expression is not based on the FACS or pre-existing literature (Section 2.1.1) – it is in essence a substitute expression contrived to compensate for the difficulty in making nose-wrinkling motions. In the FACS, the Disgust expression is primarily indicated by a "Nose Wrinkle" expression, which involves wrinkling the upper bridge of the nose along with some movement of the eyes/brows and mouth. As such, in keeping with a strict adherence to the FACS and the existing body of literature, we chose not to address Disgust at this time. The goal of the study was to evaluate a robot making facial expressions using the same minimal features a human would – how one could do so for the nose wrinkling motion in Disgust is still an open question. To our knowledge, no robotic face has yet convincingly implemented such a capability. The closest examples are the android-type faces with skin-like coverings, e.g. the Actroid-F [20] or ROMAN [23], but it is still unclear how effective these are in empirical terms (e.g. a study of the Geminoid-F did not include Disgust [21]) or how one might mimic such an effect without full-blown android faces. In short, further work is needed.

### 4.3 Future Work

Future work plans to extend upon the research described here. An ongoing study is now underway involving a series of cross-cultural experiments between Japan and the U.S. to explore cultural variability in robotic facial cues during non-verbal communication. Evidence suggests that people from different cultural backgrounds may focus on different facial features more than others (e.g. East Asians focus more on the eyes) [48-50,69]. There is also research that points to the variable significance of context as compared to the individual characteristics of the social actor [70]. These experiments will attempt to answer such questions in the scope of human-robot interaction and understand the implications for robotic face design.

Additionally, a number of other factors remain to be evaluated. Simple questions like the shape and color of key facial components, like the eyes or lips (or whether their shape/color matter at all), are still open questions. The typical assumption is that the design of biological organisms has some explicit purpose, but in reality some aspects of the design of biological organisms, including humans, may simply be vestiges of the evolutionary process, i.e. less than optimal and/or unnecessary for the purposes of artificial agents. Systematic evaluation of additional aesthetic features – ears, hair, skin – can also potentially enhance our understanding. Advances in 3D printing present new possibilities for rapid prototyping and experimentation with such components. However, a challenge still exists as to what exactly these parts should look like, which parts you actually need, and how these parts should move in a communicative robotic face. Beyond the face itself, further investigation of the myriad of effects related to body posture and gesture is also warranted. Even more broadly, several other potential variables have thus far been the subject of only limited research – e.g. saliency of context [25], interplay of human mental models with robot shape/form [71], and the effects of gaze tracking on human-robot interaction [72]. In summary, these various factors are representative of the numerous opportunities and need for future research.

**Acknowledgements**

The authors would like to thank Amyra Asamoah, Kay Jessee, and Matthew R. Francisco for their assistance in performing this research. Funding was provided by Indiana University's School of Informatics and Computing.

**References**


[1] Ekman P, Friesen WV (2003) Unmasking the Face: A Guide to Recognizing Emotions from Facial Clues. Malor Books, Los Altos, CA, USA.

[2] Cohn JF (2010) Advances in behavioral science using automated facial image analysis and synthesis. IEEE Signal Process Mag 27(6):128–133.

[3] Pantic M (2009) Machine analysis of facial behaviour: naturalistic and dynamic behaviour. Philos Trans R Soc Lond B Biol Sci 364(1535):3505–3513.

[4] Breazeal C (2003). Emotion and sociable humanoid robots. Int J Hum Comput Stud 59(1–2):119–155.

[5] Sosnowski S, Bittermann A, Kuhnlenz K, Buss M (2006) Design and evaluation of emotion-display EDDIE. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp 3113–3118.

[6] Matsumoto N, Fujii H, Okada M (2006) Minimal design for human-agent communication. Artificial Life and Robotics 10(1):49–54.

[7] Kozima H, Michalowski MP, Nakagawa C (2009) Keepon: A playful robot for research, therapy, and entertainment. Int J Soc Robot 1(1):3–18.

[8] Fong T, Nourbakhsh I, Dautenhahn K (2003) A survey of socially interactive robots. Rob Auton Syst 42(3–4):143–66.

[9] Blow M, Dautenhahn K, Appleby A, Nehaniv CL, Lee DC (2006) Perception of robot smiles and dimensions for human-robot interaction design. 15th IEEE International Symposium on Robot and Human Interactive Communication (ROMAN), pp 469–474.

[10] Chaminade T, Zecca M, Blakemore S-J, Takanishi A, Frith CD, Micera S, et al (2010) Brain response to a humanoid robot in areas implicated in the perception of human emotional gestures. PLoS ONE 5(7):e11577.

[11] Mori M (1970) Bukimi no tani [The uncanny valley]. Energy 7(4):33–35. http://spectrum.ieee.org/automaton/robotics/humanoids/the-uncanny-valley

[12] MacDorman KF, Green RD, Ho C-C, Koch CT (2009) Too real for comfort? Uncanny responses to computer generated faces. Comput Hum Behav 25(3):695–710.

[13] DiSalvo CF, Gemperle F, Forlizzi J, Kiesler S (2002) All robots are not created equal: the design and perception of humanoid robot heads. Proceedings of the 4th ACM Conference on Designing Interactive Systems, pp 321–326.

[14] Mayer C, Sosnowski S, Kuhnlenz K, Radig B (2010) Towards robotic facial mimicry: system development and evaluation. Proceedings of the IEEE RO-MAN Conference, pp 198–203.

[15] Bazo D, Vaidyanathan R, Lentz A, Melhuish C (2010) Design and testing of a hybrid expressive face for a humanoid robot. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp 5317–5322.

[16] Canamero L, Fredslund J (2001) I show you how I like you - can you read it in my face? IEEE Trans Syst Man Cybern A Syst Hum 31(5):454 –459.

[17] Saldien J, Goris K, Vanderborght B, Vanderfaeillie J, Lefeber D (2010) Expressing emotions with the social robot Probo. Int J of Soc Robotics 2(4):377–89.

[18] Delaunay F, De Greeff J, Belpaeme T (2009) Towards retro-projected robot faces: An alternative to mechatronic and android faces. 18th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), pp 306–311.

[19] Scheeff M, Pinto J, Rahardja K, Snibbe S, Tow R (2002) Experiences with Sparky, a social robot. In: Dautenhahn K, Bond A, Cañamero L, Edmonds B (eds) Socially intelligent agents. Springer, USA, pp 173–80.

[20] Yoshikawa M, Matsumoto Y, Sumitani M, Ishiguro H (2011) Development of an android robot for psychological support in medical and welfare fields. IEEE International Conference on Robotics and Biomimetics (ROBIO), pp 2378–2383.

[21] Becker-Asano C, Ishiguro H (2011) Evaluating facial displays of emotion for the android robot Geminoid F. IEEE Workshop on Affective Computational Intelligence (WACI), pp 1–8.

[22] Van Breemen A, Yan X, Meerbeek B (2005) iCat: an animated user-interface robot with personality. Proceedings of the 4$^{th}$ International Joint Conference on Autonomous Agents and Multiagent Systems, pp 143–144.

[23] Berns K, Hirth J (2006) Control of facial expressions of the humanoid robot head ROMAN. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp 3119–3124.

[24] Saint-Aimé S, Le Pévédic B, Duhaut D (2009) First evaluation of EMI model of interaction. Proceedings of the 14th IASTED International Conference on Robotics and Applications, 263–270.

[25] Zhang J, Sharkey AJ (2011) Contextual recognition of robot emotions. In: Groß R, Alboul L, Melhuish C, Witkowski M, Prescott TJ, Penders J (eds) Towards autonomous robotic systems. Springer, Berlin, pp 78–89.

[26] Esau N, Kleinjohann B, Kleinjohann L, Stichling D (2003) MEXI: machine with emotionally extended intelligence. In: Abraham A, Köppen M, Franke K (eds) Design and application of hybrid intelligent systems. IOS Press, Amsterdam, pp 961–70.

[27] http://robotic.media.mit.edu/projects/robots/mds/overview/overview.html

[28] Gadanho SC, Hallam J (2001) Robot learning driven by emotions. Adapt Behav 9(1):42–64.

[29] Ekman P (2009) Darwin's contributions to our understanding of emotional expressions. Philos Trans R Soc Lond B Biol Sci 364(1535):3449–3451.

[30] Bechara A, Damasio H, Damasio AR (2000) Emotion, decision making and the orbitofrontal cortex. Cereb Cortex 10(3):295–307.

[31] Dolan RJ (2002) Emotion, cognition, and behavior. Science 298(5596):1191–1194.

[32] Breazeal C (2009) Role of expressive behaviour for robots that learn from people. Philos Trans R Soc Lond B Biol Sci 364(1535):3527–3538.

[33] Robinson P, El Kaliouby R (2009) Computation of emotions in man and machines. Philos Trans R Soc Lond B Biol Sci 364(1535):3441–3447.

[34] Cañamero D (1997) Modeling motivations and emotions as a basis for intelligent behavior. Proceedings of the 1st ACM International Conference on Autonomous Agents, pp 148–155.

[35] Kirby R, Forlizzi J, Simmons R (2010) Affective social robots. Rob Auton Syst 58(3):322–332.

[36] Bryson JJ, Tanguy EAR (2010) Simplifying the design of humanlike behaviour: emotions as durative dynamic state for action selection. Int J Synth Emot. 1(1):30–50.

[37] Dautenhahn K (2007) Socially intelligent robots: dimensions of human-robot interaction. Philos Trans R Soc Lond B Biol Sci. 362(1480):679–704.

[38] Movellan JR, Tanaka F, Fortenberry B, Aisaka K (2005) The RUBI/QRIO project: Origins, principles, and first steps. 4th IEEE International Conference on Development and Learning (ICDL), pp 80-86.

[39] Kwon DS, Kwak D, Keun Y, Park JC, Chung MJ, Jee ES, et al. (2007) Emotion interaction system for a service robot. Proceedings of the 16th International Symposium on Robot and Human interactive Communication (RO-MAN), pp 351-356.

[40] Pollack ME, Brown L, Colbry D, Orosz C, Peintner B, Ramakrishnan S, et al. (2002) Pearl: A mobile robotic assistant for the elderly. AAAI Workshop on Automation as Eldercare, pp 85-91.

[41] Faber F, Bennewitz M, Eppner C, Gorog A, Gonsior C, Joho D, et al. (2009) The humanoid museum tour guide Robotinho. 18th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), pp 891–896.

[42] Allison B, Nejat G, Kao E (2009) The design of an expressive humanlike socially assistive robot. J Mech Robot 1(1):011001.

[43] Scassellati B, Admoni H, Matarić M (2012) Robots for use in autism research. Annu Rev Biomed Eng 14:275–94.

[44] Thrun S, Bennewitz M, Burgard W, Cremers AB, Dellaert F, Fox D, et al. (1999) Experiences with two deployed interactive tour-guide robots. Proceedings of the International Conference on Field and Service Robotics (FSR'99).

[45] Ogino M, Watanabe A, Asada M (2008) Detection and categorization of facial image through the interaction with caregiver. 7th IEEE International Conference on Development and Learning (ICDL), pp 244-249.

[46] Pantic M, Bartlett MS (2007). Machine analysis of facial expressions. In: Face Recognition. I-Tech Education and Publishing, Vienna, Austria, pp 377–416.

[47] Calder AJ, Young AW (2005) Understanding the recognition of facial identity and facial expression. Nat Rev Neurosci 6(8):641–651.

[48] Shore B (1996) Culture in Mind: Cognition, Culture and the Problem of Meaning. Oxford University Press, Oxford, UK.

[49] Yuki M, Maddux WW, Masuda T (2007) Are the windows to the soul the same in the East and West? Cultural differences in using the eyes and mouth as cues to recognize emotions in Japan and the United States. J Exp Soc Psychol 43:303-311.

[50] Jack RE, Blais C, Scheepers C, Schyns PG, Caldara R (2009) Cultural confusions show that facial expressions are not universal. Curr Biol 19(18):1543-8.

[51] Russell JA, Fernández-Dols JM (1997). The Psychology of Facial Expression. Cambridge University Press, Cambridge, UK.

[52] Fugate, JMB (2013) Categorical Perception for Emotional Faces. Emotion Review, 5(1):84-89.

[53] Anderson K, McOwan PW (2006) A real-time automated system for the recognition of human facial expressions. IEEE Trans Syst Man Cybern B Cybern 36(1):96–105.

[54] Aronoff J, Woike BA, Hyman LM (1992). Which are the stimuli in facial displays of anger and happiness? Configurational bases of emotion recognition. J Pers Soc Psychol 62(6):1050–66.

[55] Saint-Aime S, Le-Pevedic B, Duhaut D, Shibata T (2007) EmotiRob: Companion robot project. 16th IEEE International Symposium on Robot and Human interactive Communication (RO-MAN), pp 919–924.

[56] Gratch J, Rickel J, Andre E, Cassell J, Petajan E, Badler N (2002) Creating interactive virtual humans: some assembly required. Intelligent Systems 17(4):54-63.

[57] Sidner CL, Lee C, Morency LP, Forlines C (2006) The effect of head-nod recognition in human-robot conversation. Proceedings of the 1st ACM Conference on Human-Robot Interaction (HRI), pp 290-296.

[58] De Gelder B (2009) Why bodies? Twelve reasons for including bodily expressions in affective neuroscience. Philos Trans R Soc Lond B Biol Sci 364(1535):3475–3484.

[59] Russell, JA (1994) Is there universal recognition of emotion from facial expression? A review of the cross-cultural studies. Psychol Bulletin 115(1):102-41.

[60] Nomura T, Kanda T (2003) On proposing the concept of robot anxiety and considering measurement of it. Proceedings of 12th IEEE International Symposium on Robot and Human interactive Communication (RO-MAN), pp 373–378.

[61] Bartneck D, Kulic E, Croft M, Zoghbi, S (2009) Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. Int J Soc Robot 1:71-81.

[62] Hermans D, De Houwer J, Eelen A (1994) The affective priming effect: Automatic activation of evaluative information in memory. Cognition and Emotion 8(6):515-533.

[63] Henson RN, Goshen-Gottstein Y, Ganel T, Otten LJ, Quayle A, Rugg MD (2003) Electrophysiological and haemodynamic correlates of face perception, recognition and priming. Cereb Cortex 13(7):793-805.

[64] Pierno AC, Mari M, Lusher D, Castiello U (2008) Robotic movement elicits visuomotor priming in children with autism. Neuropsychologia 46(2):448-454.

[65] Ishiguro H (2005) Android science — toward a new cross-interdisciplinary framework. ICCS/CogSci Workshop: Toward Social Mechanisms of Android Science, pp 1–6.

[66] MacDorman KF, Ishiguro H (2006) The uncanny advantage of using androids in cognitive and social science research. Interaction Studies 7(3):297–337.

[67] Scassellati B (2000) How developmental psychology and robotics complement each other. Technical Report - Massachusetts Institute of Technology. CSAIL, Cambridge, Massachusetts.

[68] Barsalou LW, Breazeal C, Smith LB (2007) Cognition as coordinated non-cognition. Cogn Process 8(2):79–91.

[69] Trovato G, Kishi T, Endo N, Zecca M, Hashimoto K, Takanishi A (2013) Cross-cultural perspectives on emotion expressive humanoid robotic head: Recognition of facial expressions and symbols. Int J Soc Robot 5(4):515-527.

[70] Nisbett RE (2003). The Geography of Thought: How Asians and Westerners Think Differently ... and Why. The Free Press, New York.

[71] Powers A, Kiesler S (2006) The advisor robot: tracing people's mental model from a robot's physical attributes. Proceedings of the 1st ACM Conference on Human-Robot Interaction (HRI), pp 218–225.

[72] Sidner CL, Lee C (2007) Attentional gestures in dialogues between people and robots. In: Nishida T (ed) Conversational informatics: An engineering approach. John Wiley & Sons, West Sussex, UK, pp 103–115.