NOW YOU SEE ME, NOW YOU DON'T

revealing personality and narratives from playful interactions with machines being watched

RAY LC
City University of Hong Kong School of Creative Media

ABSTRACT

The complexity of tasks and computations undertaken by machines has grown exponentially. In order to communicate these complexities to humans working with machines, these machines must be programmed to express themselves in forms that humans can understand, not merely with procedures and numbers, but with intentions, expressive gestures that communicate emotion, and interactions that form stories, all of which can be more intuitively grasped by humans. I explored machine gestures for communicating personality and narratives by building a "shy" lamp that looks away when humans gaze closely, and follows human faces when they're far away. I followed by building a group of machines that all direct their gaze at the human unless she looks away, at which time they continue performing a skit. Artistic interventions with audiences shows playful interactions that depend on placement of the camera, showing a way of communicating machine personality using playful face-detection-based interactions.

CCS CONCEPTS

• **Interaction design**; • **Interaction design process and methods**; • **Activity centered design**;

KEYWORDS

performance, physical design, computer vision, play, social machine gestures

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1 INTRODUCTION

Machines are taking over activities ascribed to humans, from store checkouts to vehicle driving [11]. Co-evolving humans and machines leave technology outpacing communication and psychological insight. We will need to work at the boundary of self, machine, perception, and behavior, to investigate not only what makes us humans, but what makes machines machines, stepping inside the machine to see what they see [6].

The systems we create are taking actions that we can hardly grasp. An example is i2 EIA, an IBM Watson program used to identify terrorists posing as refugees, scoring the probability that an asylum seeker is truthful; border officers don't know how it operates and engineers can't isolate its parameters [32]. Virtual assistants that listen to our commands act without our explicit knowledge [5]. We often treat these devices anthropomorphically without understanding how they get and use our data [24]. Human have a hard time interpreting machine actions, especially when groups of machines perform related tasks that are difficult to interpret as a complex coordination of efforts amongst individual devices that follow different rules of interaction [33].

Voice communication between human and machines suffer from lack of nonverbal cues like gestures and emotional grounding [8]. Nonverbal and visual communication, however, in the form of gaze, or looking, makes up a majority of human emotional and physiological signaling [16, 27]. Vision leverages the physical presence of entities in human-machine systems to communicate subtle notions of trust and cooperation [3]. Both human and computer vision can interpret physical gestures, making it a useful communication strategy for collaborative physical tasks [20]. Face recognition [10] and gaze interactions [23] can provide emotional and gestural information to human and machine subjects. Thus it's critical to see how humans interpret machine expressions.

In this study, I built a machine that interacts with humans using computer vision and used an artistic intervention to investigate how humans see simple machine gestures. The machine emulates the process of "looking" in humans, taking the form of a lamp that follows human faces to light up places it looks at. But when humans get close to it, it turns away, expressing the trait of "shyness." To investigate the complexity of groups of machines in coordination, I built a group of micro-machine agents that gaze at human faces cooperatively. I varied the placement of the camera to create two sets of agents that follow different rules of interactivity. One set follows human faces using a stationary camera on the back that keeps track of view locations. When humans move out of view, the group of agents do their own thing like chatting and dancing, but when humans come into view, their locations are updated and the agents all look directly at them in 3D alignment. Another set of agents follow a single camera mounted on one agent which tracks only human face that it can see. The viewer has to actively engage the camera before the group of agents can follow. Here, the machine does not have to build a model for where the user is; it simply moves towards viewers if faces are found. This model-based vs. model-free modes of interaction can generate audience responses of flakiness, comfort, irritability, curiosity, etc., giving us a picture of how humans interpret complex coordination of group machine behaviours (Figure 1).

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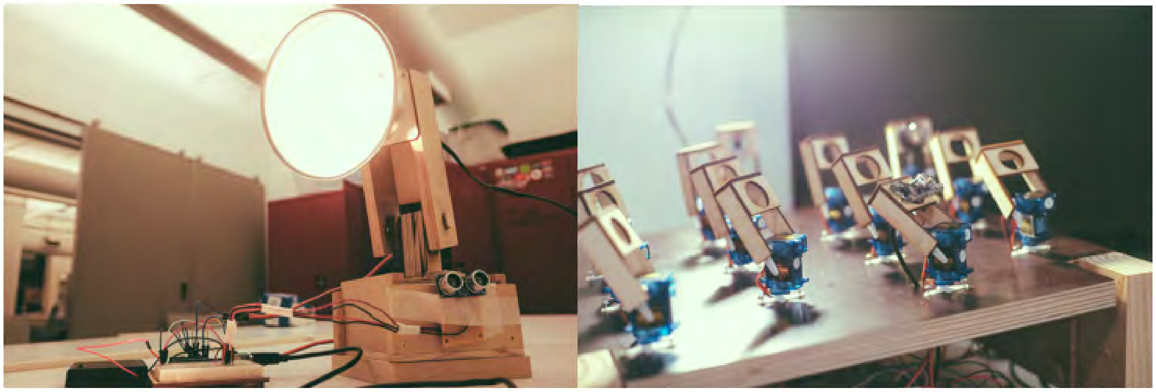

Figure 1: (Left) A machine that gazes at the participant from far away, but shies away when the audience approaches closer. (Right) A set of micro-machines that all stare at the audience when her face is detected, but go about their own agenda when the audience looks away. One set builds a model of where the face is; another set simply follow their leader.

Together, these studies show how humans and machines can communicate with each other using embodied interactions involving gaze and face detection, but more work is needed to quantify behavioural effects of these gestures and create larger-scale structures in space for human-sized gestural interactions.

2 BACKGROUND

2.1 Humans interpreting machine actions

We have long been fascinated with what machines do and ought to be doing. Asimov's laws of robotics were formulated as if robots are logical agents [1], so we can only communicate with them using logic. The laws of robotics reads like a program: (1) robot shall not harm, (2) obey humans if (1) is true, (3) protect its existence if (1) and (2). This logical interpretations of machine action have shifted in recent times to assignment of extra-mechanistic abilities to devices. When IBM Watson defeated two Jeopardy champions, it was deemed to have "ex-pert knowledge"; and when Alpha Go beat the world's best Go players, its early moves were celebrated as strokes of genius [17]. From the machine's point of view, it was the probabilistically most winning action.

Recent work has pushed the interpretations even further. In the project *Beautification*, devices using lipstick and eyeliners coupled to moving mechanisms to "beautify" human faces according to their own mechanistic logic [22], questioning the way we assign our own interpretations to what machines are doing. The notion of what machines can do has broadened from the protect-and-preserve to personality, empathy, and creativity.

The way humans has treated machines as anthropomorphic beings can be seen in research in punishment of robots, including one where perceived intelligence of the robot influenced the willingness of human subjects to inflict shock and physical hits [4]. The unwillingness of participants to break the legs of a crawling robot and their preference for indirect methods of punishment like scolding and light-flashing [25] are indicative of our automatic attribution of human characteristics like "hurt," "sad," and "vulnerable" to autonomous machines.

2.2 Humans interpreting machine intentions

Funerals have been held for Aibo robotic dogs in Japan as part of the family, with people assigning to them attributes like "active," "carefree," and "smart" [9]. Some older owners found it difficult to live without Aibos.

In the film *Her*, a man falls in love with his computer Samantha [13]. The man attributes love and romance to the relationship, but Samantha was actually talking to thousands of other users to gain knowledge with which to abandon humanity. It narrates a relationship where humans automatically assign intentions to devices.

Studies of human-machine interaction have focused on the way humans interpret the intentions of devices based on their apparent gestures. In one study, a mechanical ottoman with both functional (footstool) and personal (a pet) roles is encountered by unsuspecting subjects [31]. When the ottoman performed a lift and drop motion, it was interpreted by participants as the intention that the machine wants to stop the engagement. The participants promptly removed their feed from the ottoman. Similarly, an autonomous chair that makes a simple forward-and-backward physical gesture in front of the human was interpreted as wanting to move past the participant, i.e. "move out of my way" [14]. Meanwhile, interactions with robotic trashcans focused on human rejection signals, which were communicated by withholding of social signs [7]. Interestingly, even the strangest robots with an animated face for a monitor and speech synthesizing speakers can elicit social acceptance of their intention to fit in [34]. However human action may not square with perception, as children can interpret robots as humanoid and deserving of acceptance, but still physically abused them out of curiosity [18].

2.3 Machines interpreting human behaviors

If humans are so susceptible to machine influence, are machines also influenced by us? Face detection is used in cameras and phones to collect user profiles, and may be repurposed for influencing human behavior [35]. If we know what machines are seeing, we'll be able to critically evaluate how algorithms can be biased [21], how to

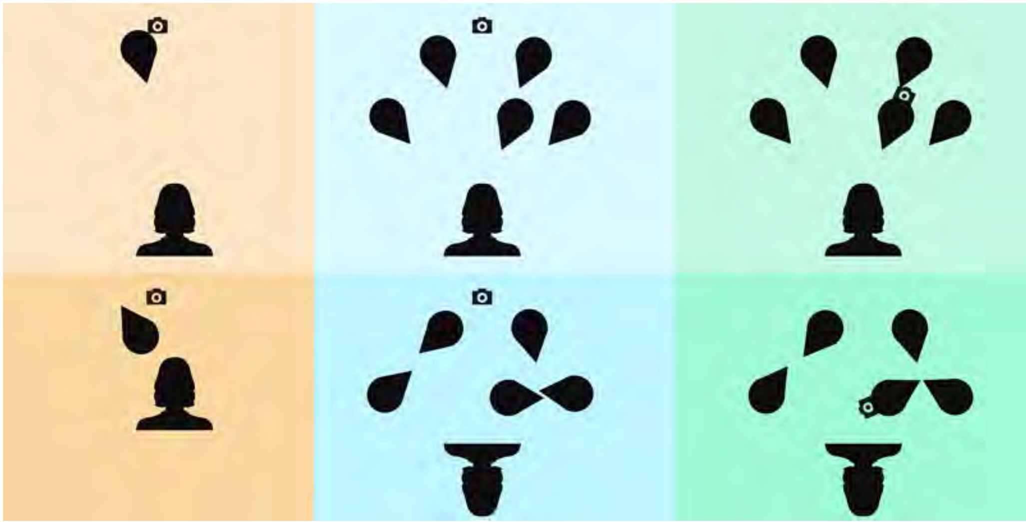

Figure 2: (Left) Single robot interaction (lamp). (Middle) Group interaction with fixed camera. (Right) Group interaction with camera mounted on the leader. Top row: when human face is detected. Bottom row: when face is close by or not detected.

escape these biases and avoid their gaze. One approach is creating machines that physically interact with humans and see, through repeated physical interactions, the biases exhibited by machines and humans [29].

2.4 Multi-agent contexts

While the majority of studies has looked at single machines or devices, it is increasingly important for humans to have an understanding of what we see in networks of devices. Do we see a family when we see a machine nurturing (tapping over) another one of the same type? Do we see a loving couple when two machines are circulating around each other? Do we see conflict when networks of IOT devices seem to be at cross-purposes? Understanding how our human view of machines in network communities with each other differ from what they are actually doing in practice provides a way to identify our own perceptual biases.

Work with a group of robots shows that robot ensembles are capable of making people conform to their collective answers in a game where they choose a card that best represents a particular word [28]. This version of the Asch experiment shows that robots have collective presence just as humans. Robot groups can also collaboratively accomplish tasks like disassembling to move past a fence or swarming together in different patterns on a terrain [19]. However more research is needed to understand human perception of these swarms.

My Keepon are robotic plush toys that pan, tilt, and roll, evoking human features that notate group behaviour [2]. Coordinated movements amongst robots can tell a coherent story. *Penguins Mirror* is a work of 450 robotic penguins that rotate so as make out the shape of the viewer's body en masse [26], and *Audience* is a room of tiny mirrors that each look up and follow a human when she visits, reflecting herself [12]. These work, are interactive only in the way they gaze at us. To study how devices with agency and personality interact with humans, I created machines that exhibit different behavioural patterns when they are being looked at vs. ignored.

3 METHODS AND OUTCOMES

3.1 Single robotic agent

Since we stare at our devices (computers, phones, TVs) all the time, how would we feel if they stared back at us? To study how humans interpret simple gestures of machines being watched, I built a lamp which tracks the human face from afar, but which turns away when humans get near (Figure 2 Left). The base of the lamp rests on a rotating platform with a servo motor attached to the base for panning. Another servo motor provides the tilt by moving the head of the lamp towards the ground or the sky. The light bulb is mounted on the bulb holder attached at the stalk of the lamp, and connected to a light dimmer module. An Arduino Uno board attaches to the dimmer, the servo motors, and an ultrasonic distance sensor (Figure 3). The servos are powered by external AA batteries, while the Arduino connects to the computer via USB. The computer is also connected an external webcam, which is placed next to the lamp. The Processing code on the computer runs OpenCV to detect faces in the scene. When the face is found off center of the camera, Processing sends a command via serial communication with the Arduino to move the panning and tilting motors incrementally to return the face to the center of the view. Meanwhile the ultrasonic sensor captures the distance from the human to the lamp, and interrupts the process to move the motors so that the lamp turns away if the human is closer than approximately 1.6ft. In a later iteration, I also used the size of the face detected in OpenCV to determine when to turn away.

Next I deployed the robot and allowed students from Parsons School of Design play with it individually without instruction (n=11, 7 female, ages 20-32). I recorded (1) how people interacted with it in use of gestures, (2) subjective experiences with the lamp in interview and survey form (Likert scale 1 to 7) in expressiveness and

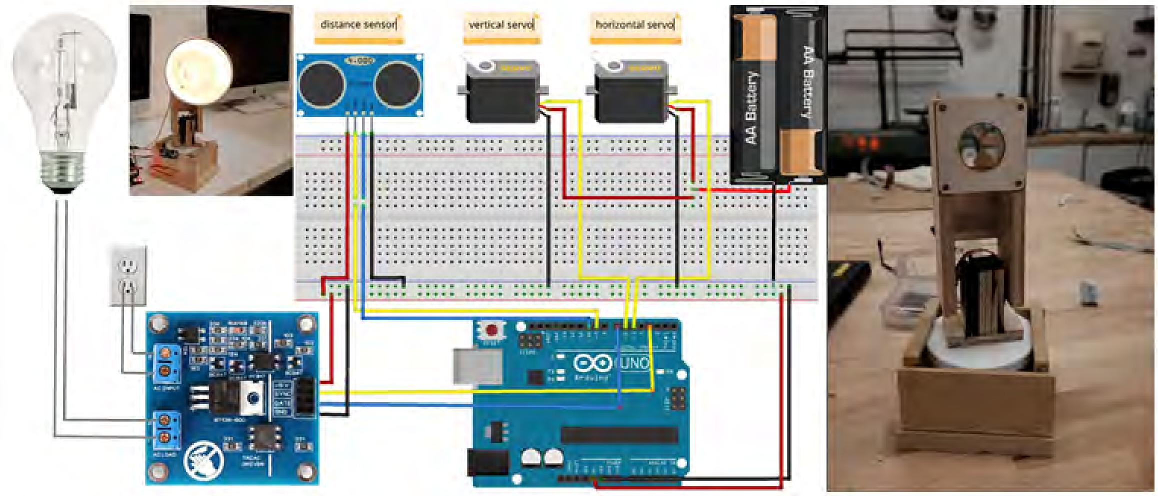

Figure 3: (Left) Connection diagram of lamp system (Not shown is the computer, which is connected to the Arduino and to an external webcam placed next to the lamp). (Right) Skeleton of the lamp body: a servo motor sits under the lazy susan.

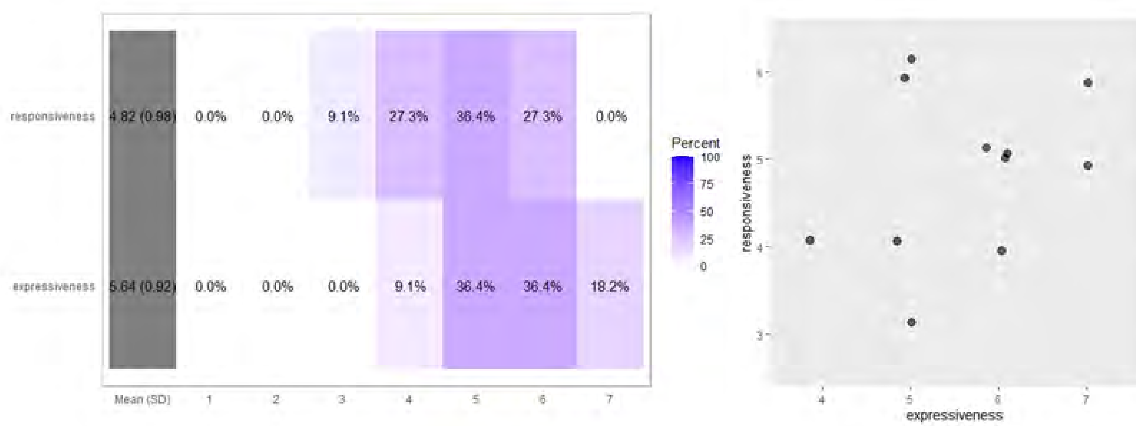

Figure 4: (Left) Heat map of responses to 1-7 Likert scale question of "how responsive was the robot?" and "how expressive was the robot?" with 1 "not at all" and 7 "extremely" (n=11). No significant difference between results from the two questions (Wilcoxon signed rank p>0.05). (Right) Scatterplot with jittered responses (for visualization). Polychoric correlation R=0.4.

responsiveness. The former measures how useful the lamp's gestures are in conveying the personality trait of "shyness," while the latter measures how well the physical mechanisms of the machine is able to implement the trait (Figure 4). No significant difference was found between the two responses (Wilcoxon signed rank p>0.05).

In qualitative observations, I found that audiences invented some unexpected ways of interacting with the lamp. One girl crawled under the table on the left side and emerged on the right side, where the lamp quickly moved to follow her face. This gives the impression that the lamp is all-knowing from afar. But at medium distances, participants described the lamp as curious, as it continues to track their faces. Another unexpected gesture that gave the impression of curiosity is switching between audiences when multiple participants are in the room. The lamp has no preference for one face or another and hence would move from staring at one face to another. A personality trait hence emerged from the omission of control for a particular situation (Figure 5). In one episode, a participant figured out that to make the lamp shy away, he doesn't have to move his body, but rather reach out with his hands to interrupt the path of the ultrasonic sensor. This makes the lamp slavish as opposed to shy. To correct for this, I used the OpenCV face rectangle size to determine when to shy away instead of the ultrasonic sensor. Perhaps the clearest insight is how much fun participants had with the lamp, as its combination of curiosity and shyness led to one participant calling it "cute" and wanting to take it home.

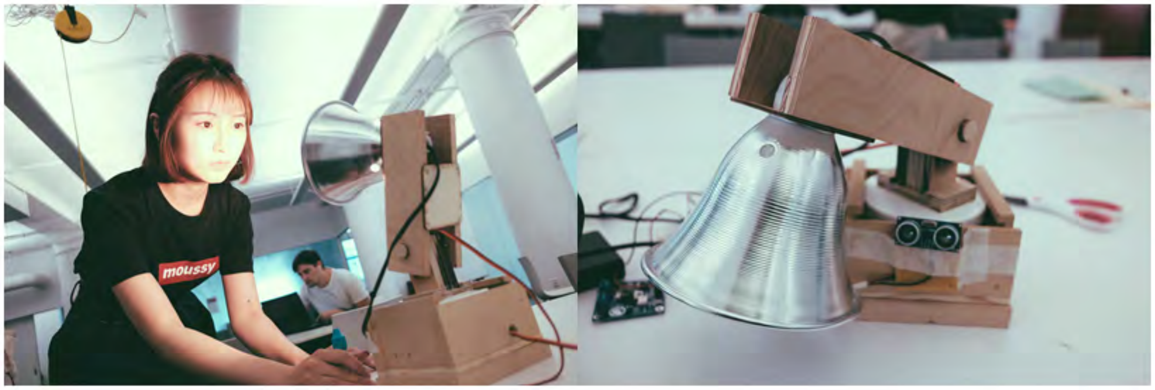

Figure 5: (Left) A participant interacting with the lamp. (Right) Lamp in crouched position showing shyness.

Figure 6: (Left) A participant interacting with the flock before being detected. (Right) The flock converges on detected face.

3.2 Robot groups in narrative

It's easy to surmise interactions with one machine, but what if a set of machines stared back at us? There's an immediate sense of being watched and conformity evoked by increasing the numbers. What does a network of unified or contrasting machines evoke in us? Will we see their individual personalities, agencies, and stories? I made a flock of pan-and-tilt machines based on the design of the lamp that are connected to a single camera for tracking human faces. Instead of distance, the variable of interaction was whether a face is detected. The metaphor was that when humans are not looking, the machines have their own secret lives, and stories to tell. When human face is seen, all the machines in the flock look at it in solidarity, evoking curiosity (Figure 6).

Two groups of agents following different rules of behaviour initially. One set (Figure 2 Middle) follow human faces using a stationary camera on the back of the platform that keeps track of view locations. When the user moves out of view, the group of agents start chatting and dancing, but when faces come into view, their locations are updated and the agents all look directly at them in alignment. Another set of agents (Figure 2 Right) follow a single camera mounted on one agent which tracks only the human face that it can see. Here, the viewer has to actively engage the camera before the group of agents can follow her. The machine doesn't have to build a model for where the user is; it moves towards the viewer if a face is found in the field of view of the leader.

This distinction between the two groups of machines is the model-based vs. model-free AI algorithms found in artificial intelligence research [30] (Figure 7). The former constructs a model predicting where human faces are found and responds decisively when one is found, but it cannot generalize well in new situations where the terrains are different for the calculations. The latter keeps track only of a way of moving towards faces, a heuristic that moves itself to the right when a face is detected in the left side of the pixels, etc. It can't detect all faces in the environment, but it can generalize to any situation where faces exist, even outside the platform.

When audiences interacted with the system, they noticed that the model-based system can track their face fairly reliably, albeit after a slight delay. They often call it "cute but creepy," but when I turned a few of the agents of the model-based system into ones that do their own tasks without tracking faces, viewers find it much more natural and non-threatening, much like a "cute flock of owls." Although users had the most trouble with the model-free system (the agent with the camera attached and its associated followers),

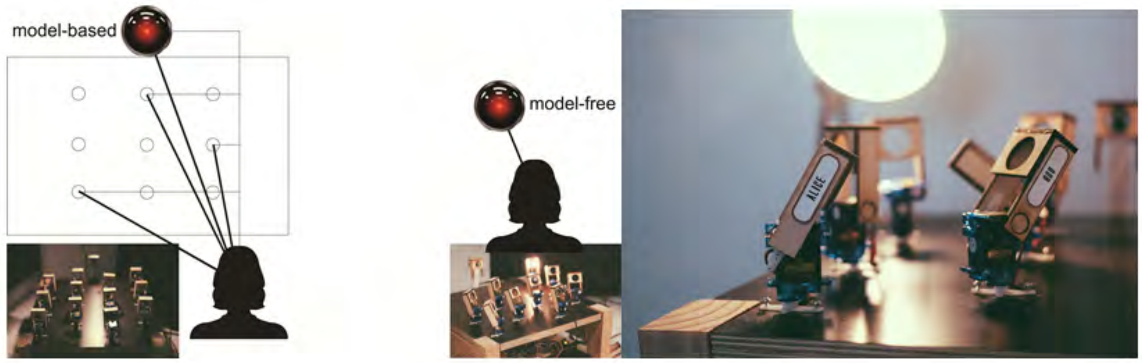

Figure 7: (Left) Model-based vs. model-free calculations of where the viewer is. (Right) Alice and Bob meeting and making a back-and-forth motion in a Romeo and Juliet story only when no audience faces are detected (or faces are hidden).

surprisingly they found it the most temperamental and "human-like." Perhaps it is because that system forces the user to move their face into the agent's field of view in order to be tracked, so the users are forced to "get the robot's attention," much as "prima-donna" type personalities in the real world. This mixture of a "self-centred" model-free system and a "reliable" model-based system give the users the richest experience where the members of the flock appear to show emotionality to those interacting with them. Viewers also invented playful games on their own, including two players showing their faces one at a time while giving hi-fives; and another playing "hide-and-seek" with hands over their faces as long as possible while facing the camera and escaping detection (see Video).

For human interaction, I programmed the systems to perform a script when no faces are detected. For example, I produced a "Romeo and Juliet" script in which "Alice" and "Bob" agents shyly stand next to each other "in public" when their compatriots are tracking viewer faces. When viewer faces are not found, the other agents do their own activities, and "Alice" and "Bob" are able to "meet" (i.e. turn towards each other) and consummate their love. It took a few attempts for viewers to understand this, but once they did, they found the story amusing, and began assigning emotionality to behaviours of the flock that depend on their interactions with us. Eventually they gave labels to these characters in the play and I put stickers on their frames like "Hope," "Vanity" (for the leader), "Slacker," and "Paparazzi." The act of seeing has engaged a new dynamic in the network where characters alter their connections with each other based on audience interaction.

4 DISCUSSION

Using single and groups of machines, I showed how personalities and stories emerge from playful "looking" interactions with machine gestures. Artistic interventions allowed us to examine machine behaviours amongst themselves as well as behaviours synchronized in some way to us. We begin to see personalities like curiosity and shyness; and relationships like flocking behaviour reminiscent of birds, internal conflict of fractions within the group, the rebellious maverick of the group, even love, care, or desire play out in narrative form.

One of the main lessons learned is that human affection can be won by simple mechanical gestures. By applying a "look at" gestures and "shy away" gesture to the lamp, humans assign emotional significance to the interaction. In particular, they rated the machine as highly expressive, even more important than its mechanical responsiveness. This promises expressive potential of machines by tailoring their behaviours to those designed to couple with the social cognition of human observers as opposed to only functional gestures for work. When machines take actions in a group, I found that new issues like presence, trust, and role-play become variables of interaction. The issues of virtual and physical presence [3], trust and conformity [28], and educational role-play [15] in the context of group robotics have begun to explore the potential for collective action of robots to influence human perception and action. I learned in this study that in addition to leveraging social influence, the increasing number of robots allow us to tell rich stories that depend on human interaction, providing a natural avenue for spontaneous play. These interactions differ depend on whether they are calculated based on a model for each machine (like dynamic programming), or on immediate action rules (like Q-learning).

Future work will account for imitations of testing for the machine flock. Measurement of biometric response and quantitative analysis of human gestures during interactions can provide more specific data on human perception. We would also benefit from a build for life-sized interactions to reveal everyday human gestures.

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