Building artificial personalities: expressive communication channels based on an interlingua for a human-robot dance

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Abstract

The development of artificial personalities requires that we develop a further understanding of how personality is communicated. This can be done through developing human-robot interaction (HRI). In this paper we report on the development of the SpiderCrab robot. This uses an interlingua based on Laban Movement Analysis (LMA) to intermediate a human-robot dance. Specifically, we developed measurements to analyse data in real time from a simple vision system and implemented a simple stochastic dancing algorithm on a custom built robot. This shows how, through some simple rules, a personality can emerge by biasing random behaviour. The system was tested with professional dancers and members of the public and the results (formal and anecdotal) are presented herein.

Introduction

Can the study of human-robot interaction lead to the development of embodied agents with emergent *artificial personalities*? We define an artificial personality as a machine that is (and was been intentionally built to be) socially interactive. Socially interactive robots should:

> "express and/or perceive emotions; communicate with high-level dialogue; learn models of or recognize other agents; establish and/or maintain social relationships; use natural cues (gaze, gestures, etc.); exhibit distinctive personality and character; and may learn and/or develop social competencies." (Fong et al., 2003; Dautenhahn, 2007)

Focusing on studying systems that express and perceive emotion, we must understand the principles of emotional communication. We focus here on non-verbal communication as much human-human communication is done through body language (Mehrabian, 1981): i.e., communication which is expressive in its nature. In the spirit of ALife research, we look for simple models that are hopefully applicable across a broad range of systems.

Considering expressive human movement, we take our inspiration from analysis of dance—an art-form of expressive human movement. Dance, and specifically expressive movement quality in dance, has been studied in detail (Laban, 1971; Laban and Lawrence, 1974). We therefore both explore the principles of dance to outline potential models of expressive communication and also test those models by embodying them in a dance context.

Attribute	Description
Simple	The protocol for communication between agents should use a tractable mechanism
Expressive	The protocol should be identifiable by humans as containing emotive human content
Embodied	The protocol should work in an embodied system—we use an improvisational dance

Table 1: The attributes required for our development of communication channels for an embodied artificial personality

We specify the important attributes for our models of communication channels in Table 1. These three attributes (*Simple*, *Expressive* and *Embodied*) are important in the production of an artificial personality. We outline three communication channels in this work and discuss them in light of the attributes given in the table.

From a broader scope, we also consider the relevance of the communication channels we have identified to an evolutionary or ALife perspective. Many artificial life projects look for *emergent communication* [see work by Quinn (2001), Marocco et al. (2003) and Nolfi (2005) for examples], where a new communication channel emerges in a system without any prior specification. Such emergent communication channels are interesting from an evolutionary perspective as they can define simple mechanisms by which communication can occur with very little extra function being developed. A sociobioligical definition of communication (Wilson, 1975) sheds further light on the topic:

> "Communication occurs when the action or cue given by one organism is perceived by and thus alters the probability pattern of behavior in another organism in a fashion adaptive to either one or both of the participants." (p. 111)

Category	Description
Body	Studies the way an individual uses their body joints to generate movements
Space	Studies the way an individual interacts with space outside the body
Shape	Studies the sorts of shapes made by individuals as they move
Effort	Studies the way an individual moves

Table 2: The four LMA categories.

Subcategory	Description
Space	Is the movement direct or indirect
Weight	Is the movement strong or light
Time	Are the movements quick or sustained
Flow	Are the movements under body control (bound) or are they allowed to flow

Table 3: The four subcategories of the LMA effort category.

Given this definition there need be no intentionality on the behalf of the sender to transmit a signal—thus a communication channel may emerge just from observations of another's behaviour. We consider whether the expressive channels of communication developed here are relevant as forms of emergent communication.

Dance background

The field of postmodern dance stands out as being particularly relevant to the direction of study outlined in the previous section. Other dance forms, such as ballet, focus on structured movements. Ballet dances are commonly formed from a grammar of dance positions called *Key Aesthetic Poses*. Expression is conveyed through changing the style of movement between each dance position. Alternatively, postmodern dance seeks to remove all syntax and structure from dancers movements (Banes, 2003). Dancers are taught to unlearn their usual movement vocabulary so they can move on a purely expressionistic level. Commonly, dancers improvise in pairs (or greater numbers) where they each either *copy*, *oppose* or *innovate* qualities from the other's movements. Since their movements are no longer consciously motivated they therefore become examples of emergent communication.

We look here at a method which is widely used for interpreting and understanding expression qualities in dance (Laban, 1971; Laban and Lawrence, 1974): Laban Movement Analysis (LMA). This has four main categories which are outlined in Table 2. As we are focused on movement quality, we looked more closely at the effort category, which has four subcategories outlined in Table 3.

In a modern improvisational dance context, the dancers make *offers* to each other through their movement quality. From an LMA perspective, movements can be classified and dances can be interpreted through this language. In improvisation, movement quality is often copied with occasional innovations and oppositions—this gives the dancers a sense of *performative merging*.

Other work

Previous work for generating expressive movements has focused on a computer model of the human arm and torso (Chi et al., 2000) and a computer model of a ballet dancer (Neagle et al., 2004). In both systems, key positions and times were defined for body parts and heuristics, inspired by LMA, were specified for movement between positions. An important factor was found to be the velocity profiles of movement (Neagle et al., 2004).

The analysis of expressive qualities of human movements has been attempted before (Castellano et al., 2007). This approach used features generated from many different movement characteristics (Acceleration, Contraction Index, Fluidity, Quantity of Movement and Velocity) taken from actors making gestures expressing one of four emotions (Joy, Anger, Pleasure and Sadness). Various *classifiers* were tested with the data in order to generate models which would identify the correct emotion using the features available. The most significant feature was found to be Quantity of Movement with the Contraction Index (the degree of contraction and expansion of the body) playing a minor role. However, the system was not able to classify all emotions accurately. The complexity of this approach is not compatible with our requirement that models be tractable (Table 1) because of the large number of features used by the classifiers.

The SpiderCrab system

Given analogues between LMA (see the Dance background section) and mathematical analysis, and success using it in the past, LMA was chosen to act as an *interlingua* for an improvisational human/robot dance. The SpiderCrab robot was chosen to embody an artificial personality developed within the requirements of Table 1. The design phase of the robot was done through embodying it (into human form) at dance workshops. This was, in part, to study the application of performance arts methodology to the design process (Bayliss et al., 2007). It was also useful to form a picture of how the robot may be capable of expressive behaviour. In this project we focused specifically on the development of a controller for the robot to explore its potential as an improvisational dance partner.

An overview of the system we developed is presented in Fig. 1. The Robot system has three subsystems: the *sensory input*, *robot controller* and *improvisation* subsystems. Both the sensory input and robot controller subsystems use the *expressive communication model*, which is a common framework, based on LMA, for classifying both input from the dancer and output to the robot. Decisions about how the robot should react to different sensory inputs from the dancer were made by the improvisation subsystem.

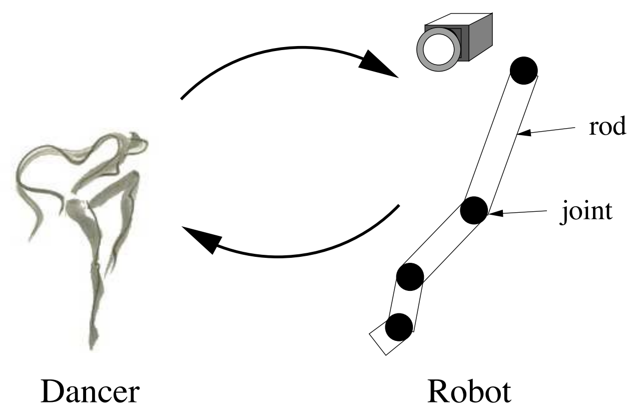

Figure 1: An overview of the SpiderCrab system showing expression flowing within a closed loop between the dancer and the robot. The robot system controls the robot, responding to the quality of the dancer's movement by biasing the robot's random movements. The dancer responds to the robot's movement.

The expressive communication model

The expressive communication model uses LMA to provide a common language for dancer and robot movement. For simplicity we focus on only one primary subcategory of LMA and analyse its role in the expression and communication of emotion. We chose the *weight* subcategory in the *effort* (see Table 3) category for several reasons. Previous work (Neagle et al., 2004) has shown that it is possible to generate movement in a virtual dancer in which humans can distinguish three emotions: Sadness, Happiness and Anger. These same emotions can also be distinguished when human dancers perform movements on different regions of the weight subcategory spectrum.

Two secondary subcategories of LMA were also considered, to try and understand their roles in the expression of emotion. These were the *space* subcategory (see Table 3) which is in the *effort* category and the *kinesphere* subcategory in the *space* category. The kinesphere subcategory relates to the area the dancer is moving within and how that relates to other dancers.

The two Effort subcategories were modelled as three discrete nouns (see Table 4). The kinesphere subcategory was modelled as a 3D coordinate which represented the position of the armband, and the 3D locations of the joints and rods of the robot limb.

Sensory input subsystem

A simple vision subsystem was used to generate real time data for our system. Some bright green material was fixed to the dancer (often as an armband) and its location was tracked

LMA subcategory	Settings
Weight	Strong; Medium; Light
Space	Direct; Indirect

Table 4: The two subcategories of the LMA Effort category can have different settings in the expressive communication model. An LMA noun can be formed by choosing a setting from each subcategory, e.g., Strong+Direct would mean strong, direct movements.

by digital cameras. We recorded the centre of the green pixels at each timestep on each camera's image and this coordinate $[x(t), y(t)]$ was used to generate measurements for each camera.

Measurements were taken using the values of $x(t), y(t)$ to model the two LMA effort subcategories, weight and space. First, we propose that the LMA subcategory weight of movement may be modelled by the power delivered to the armband over a period of time of length T. This is approximated by assuming the mass of the armband is 1.0 (we do not use standard units). The force on the armband is thus equal to the absolute value of the acceleration of the armband at the camera frame. The power over time T is given by,

$$power(t) = \frac{1}{T} \sum_{t-(T-1)}^{t} Fl \ , \tag{1}$$

where F is the force on the armband at t and l is the distance travelled by the armband over the timestep at t. An alternative measurement was also considered, the average absolute speed over time T,

$$speed(t) = \frac{1}{T} \sum_{t-(T-1)}^{t} |s| \ , \tag{2}$$

where s is the speed of movement of the armband at time t.

The indirectness of movement was also considered to model the space subcategory. To do this, the direction of movement θ was calculated at each timestep. The rate of change of direction can be approximated by taking $d\theta/dt = \theta(t) - \theta(t-1)$. We introduce an indirectness measure over a period of time T which is given by,

$$indirectness(t) = \frac{1}{T} \sum_{t-(T-1)}^{t} \left| \frac{d\theta}{dt} s \right| \ . \tag{3}$$

Our $indirectness$ measurement is greater when the armband changes direction while moving quickly.

When the robot was in improvisational dance mode, the time period was set to two seconds for the $power$ measurement and one second for the $indirectness$ measurement. For evaluations of the Sensory input subsystem, movements of the dancers were broken down into gestures and the measurements were calculated for each gesture. Gestures were

Joint	Degrees of freedom	Rod length (m)
Shoulder	2	2.10
Elbow	2	1.30
Wrist	2	0.80
Finger	1	0.53

Table 5: The four joints of the SpiderCrab robot. The joints are connected in sequence. The Shoulder joint is fixed to the environment with each following joint connected by a sturdy rod.

identified by looking at the acceleration time trace: gesture start and end points were taken from when the acceleration moved from negative to positive values. Very short gestures ($<$ 0.6 seconds) were combined together into longer gestures.

Tests with a simple 2 camera setup did not produce accurate enough 3-dimensional locations for the $power$ and $indirectness$ measurements. So we estimated motion orthogonal to the viewing direction of each camera using position in the image and assuming a fixed depth. This is a reasonable approximation assuming the dancer would stay roughly the same distance away from the cameras and face the cameras, although it will not include contributions to power and indirectness that arise from motion in depth. Course grained 3-dimensional location information was generated for the kinesphere aspect of the Expression communication model by using a second camera and triangulating the position.

The robot and the robot controller subsystem

The robot[1] is a single limb with four joints, see Table 5. The robot was designed to interact with the public, so needed to be as light and flexible as possible. The four joints of the limb are thus moved using air muscles with each axis of rotation having a pair of air muscles—a flexion muscle and an extension muscle. Valves connected to the air muscles are computer controlled, letting air in or out and contracting or extending the muscle respectively. Sensors on each joint return its angle(s) to the controller.

The quality of movement of the robot is defined by one of the six LMA nouns given in Table 4. The current LMA noun is received from the Improvisation subsystem (see the next section for more details on the Improvisation subsystem).

To control the robot's quality of movement, three variables are changed according to the LMA noun received from the Improvisation subsystem: $joint\_instruction\_length$, $robot\_movement\_power$ and $joint\_direction\_consistency$. A pair of air muscles rotate the joint around an axis of rotation for a random period of time (selected from a flat distribution between 0 and 1) multiplied by the $joint\_instruction\_length$. The amount of air fed to the muscles (per second) is sampled randomly from a uniform distribution between 0.5 and 1.5 and multiplied by the $robot\_movement\_power$. At the end of each movement the joint either continues its rotation in the same direction or will reverse direction with a probability depending on the $joint\_direction\_consistency$. If at any time a joint rotates past a limit (commonly the maximum rotation of a joint), the rotation direction will be reversed.

The three variables were set by hand for each of the six LMA nouns. They were tuned by assessing the robot's movement by eye. The $robot\_movement\_power$ variable corresponded with the weight subcategory, and the $joint\_instruction\_length$ and $joint\_direction\_consistency$ variables corresponded with the space subcategory.

The other important aspect of the robot's movement is determined by the kinesphere subcategory of the LMA space category. Here the robot will either point the elbow joint toward the dancer's general location, or ignore the dancer's general location and move the elbow freely. When the elbow must point, it rotates toward the target with an angular velocity proportional to the target's angular distance from the rod extending from the joint.

Improvisation subsystem

The robot was designed to perform within a postmodern dance improvisation context. This means that the robot will embody the expressive communication model by interfacing between the sensory input module and the robot controller. The improvisation subsystem implements an improvisational dance by switching between three different modes: Copy, Follow-copy and Oppose. Table 6 describes the three modes.

Improvisation mode	Description
Copy	The robot movement quality directly copies the movement quality of the dancer (using the effort and space subcategories of the LMA effort category)
Follow-copy	As **Copy** but with the elbow joint pointing at the dancer (using the kinesphere subcategory of the LMA space category)
Oppose	The robot movement quality is the opposite to that of the dancer (using the effort and space subcategories of the LMA effort category)

Table 6: The robot responds to the quality of movement of the dancer by selecting an LMA noun depending on its improvisation mode.

[1]The robot was designed in partnership with, and built by, the Shadow Robot Company. See `http://www.shadowrobot.com` for further technical information.

The $power$ and $indirectness$ measurements were used to identify which LMA noun the dancer was using. When in copy mode the dancer's noun was output to the robot controller, when in oppose mode, the opposite noun (i.e., Strong → Light, Light → Strong and Direct → Indirect) was output to the robot controller. The robot cycled through the 3 modes spending 30 seconds in Copy mode, 30 seconds in Follow-copy mode and then a random number of seconds (between 5 and 15) in Oppose mode.

Essentially, the robot responds to three key elements measured from the dancer's movement: the weight of movement, the directness of movement and the location of the dancer. It responds by either producing movements with a similar quality, or by producing movements with an opposing quality.

Evaluation

The SpiderCrab system was evaluated from two perspectives. First, we focused on the sensory input subsystem to evaluate its capabilities of perceiving emotional quality in movements. Second, the full system was evaluated by members of the public and dancers from the Salamanda Tandem dance company.

Sensory input subsystem evaluation

We tested the Sensory input subsystem over two dance sessions. In the first session the dancer was asked to make the same gesture with different qualities of movement. In the second session the dancer moved freely making varying gestures to different qualities of movement. Evaluations are made with reference to the attributes required by Table 1.

In both sessions the dancer stood at a fixed distance from a single camera. Approximately 20 gestures were made for each movement class by both dancers.

In the first session, we considered whether the sensory input subsystem was capable of assessing the emotional content of a dancer's movement (the Expressive attribute in Table 1). Dance movements were taken from three different movement classes expressing the three different emotions: Sadness, Happiness and Anger. For each individual gesture, the power and speed measurements (see Eqs. 1 and 2) were calculated using the Sensory Input subsystem. Box plots of the power data, collected within each movement class, are shown in Fig. 2. Box plots of the speed data, collected within each movement class, are shown in Fig. 3.

Figure 2 shows that the power measurement is a good choice for the Sensory Input subsystem to distinguish between the three emotions expressed by the dancer. In fact, the mean absolute acceleration also worked well (not shown). We decided to work with the power measurement as it relates more closely to our sensations of moving in the three movement classes: in an *ad hoc* experiment, the perceived work done by our muscles when expressing the emotions correlated with the power recordings of Fig. 2. An

Figure 2: The same gesture made with movement quality expressing different emotions. The Sensory Input subsystem can distinguish between different emotional qualities of movement by calculating the power (see Eq. 1) delivered to the armband. Two-sample t-test comparisons between the three movement classes all give $p < 7.7 \times 10^{-05}$.

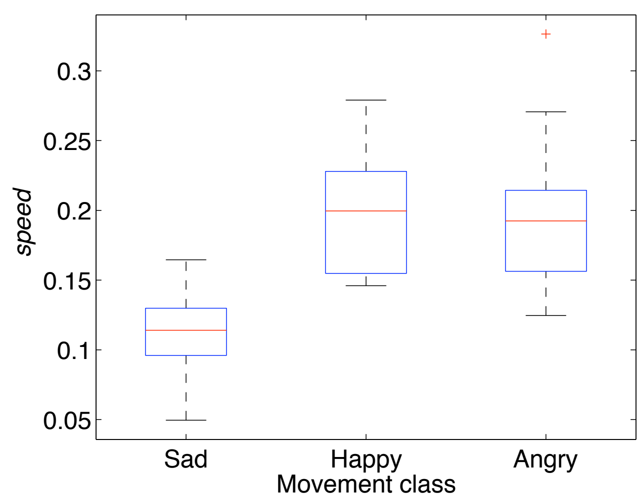

Figure 3: The same gesture made with movement quality expressing different emotions. The Sensory Input subsystem is unable to distinguish between the Happy and Angry gestures when calculating the average absolute speed (see Eq. 2) of the armband. A two-sample t-test comparison between Happy and Angry gestures gives $p = 0.82$

alternative measure of considering the average speed (or, by extension, momentum) of the armband did not distinguish between the Happy and Angry gestures (Fig. 3).

In the second dance session, a dancer was asked to perform gestures freely with relevant LMA nouns of the weight and space subcategories of the effort category. This formed four classes of movement: Strong+Direct, Strong+Indirect, Light+Direct and Light+Indirect. The output of the power measurement for the strong and light movements is shown in a box plot in Fig. 4. The output of the indirectness measurement for the direct and indirect movements is shown in a box plot in Fig. 5.

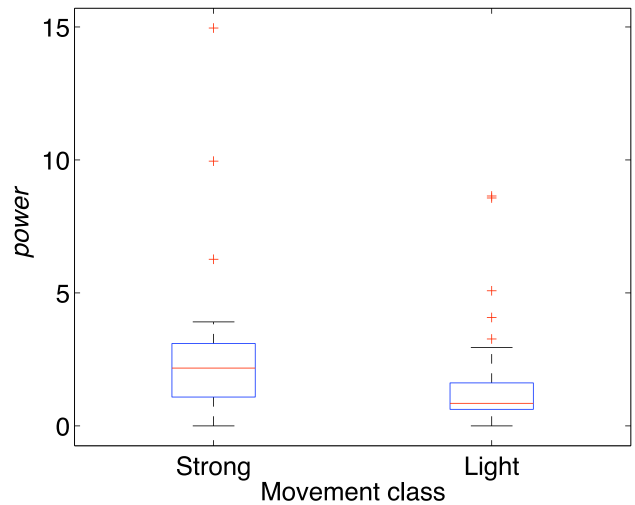

Figure 4: Varying gestures made with strong and light LMA movement qualities. The Sensory Input subsystem can distinguish the quality of movement by calculating the power delivered to the armband. A two-sample t-test comparison between the two movement classes gives $p = 0.018$.

The Sensory Input subsystem was able to distinguish between strong and light movements (see Fig. 4). In comparison to Fig. 2, some gestures were of a much greater power. Greater power can be delivered to the armband when the individual moves their body as well as their arm, rather than just the arm on its own. While the system had some success in distinguishing direct and indirect movements, the results were not significant. This was because it could not distinguish between an individual moving to start a new gesture (not relevant within and LMA context) and an individual moving within a gesture).

Full system evaluation

We evaluated the full system based on an embodiment test for an artificial dancer partner proposed by Wallis et al. (2007). This argues that "success will be measured by whether or not the human dancer feels that he/she is dancing with a true partner". With this in mind, we evaluated the

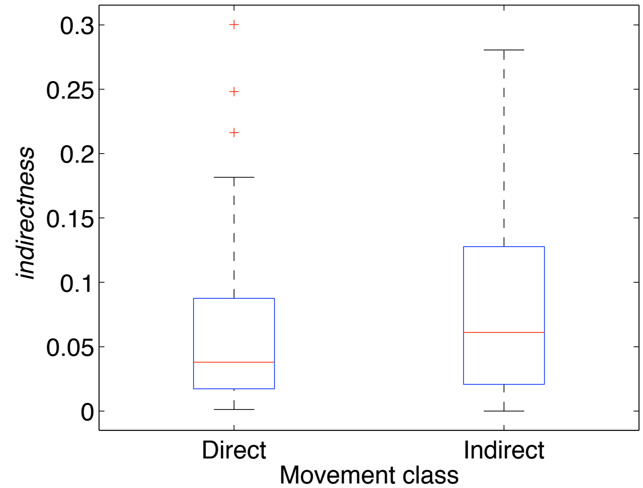

Figure 5: Varying gestures made with direct and indirect LMA movement qualities. The Sensory Input subsystem is unable to distinguish between the two movement classes. A two-sample t-test comparison between the two movement classes gives $p = 0.32$.

robot using a professional and independent dance company that focuses on improvisational dance. The company, Salamanda Tandem, use dance as a means of studying and developing social interaction—particularly with disabled people including those on the autistic spectrum.

Dancers from the company danced with the robot (see Figure 6) over a period of two days and wrote a report (Jones and Hood, 2008) on their interaction with the robot. So that their experience was not biased in any way, the dancers were told as little as possible about the way the system worked before starting to dance, just that it would respond to movements with the green armband.

Their responses to dancing with the robot indicate that it had passed the embodiment test: the robot did feel like a true partner. One of the assessors stated that

> "I felt apprehensive when approaching to move with the robot but it's amazing how quickly I forgot it was a robot and was just dancing with another, it felt friendly" (Julie Hood).

Another dancer felt that

> "[a]t first it's like a robot, then you forget and you are having a duet, getting to know someone—shaking hands... You can build a connection in play and be imaginative with it... It becomes a human limb" (Mickel Smithen).

In general, when the robot was in the copy mode people dancing with the robot (both professional dancers and members of the public) felt that it was responsive to their expressive offers. This meant that there was a bi-directional

Figure 6: A dance student dances with the robot.

expressive communication channel. When noise was introduced so that the system responded erratically (detecting movement when none was there), dancers felt it was less responsive.

Some comments picked up on how we might develop the robot's personality:

> "I've noticed in my work with people that there needs to be a pace, a sense of timing to encourage interaction to take place...I believe that SpiderCrab would need to be able to vary [its timing] in response to different sorts of people" (Isabel Jones).

Development along these lines could mean that the SpiderCrab system could become

> "a fantastic tool to deconstruct and analyse human interaction" (Isabel Jones).

After a while, the dancers started to feel that the robot's behaviour was becoming a little predictable and that its quality of movement was limited when compared with a human dancer.

The Sensory Input subsystem was shown, in the previous section, to be able to distinguish between movements expressing different emotions. When the robot was placed in an environment with real dancers, the robot was clearly able to pick up on the weight of the dancer's movement of the armband.

While there is a long way to go before the robot can fully identify the dancers' movement qualities, the six different qualities of robot movements were, however, qualitatively identifiable from each other. Reports from dancers were that robot movements could range from "menacing" to "smooth".

When the robot's elbow joint pointed toward the dancer's location, we had mixed responses. For safety reasons we had to slow the movement of the elbow. This meant that the robot was slow to copy the dancers' movements. Some dancers did not notice the difference between the copy mode and the follow-copy mode. However, when the follow-copy mode was observed, some dancers felt that the robot was crowding them whereas others felt that the robot was being more friendly.

Discussion

In this project, we have developed a robot system that, through improvisational dance, is capable of bidirectional expressive communication. The SpiderCrab system can distinguish between different human emotions, based on the quality of movement. Furthermore, the robot's movements were responsive to the dancers' movements and interpreted as such by the dancers. This meant that the robot was successful as an improvisational dance partner and was able to achieve social interaction [as specified by Fong et al. (2003); Dautenhahn (2007)] through the embodied expression and perception of emotions.

To consider the robot's potential as an artificial personality, we review the communication channels used by the system in light of the attributes outlined in Table 1. Starting with the primary communication channel, the power measurement (see Eq. 1) does indeed satisfy all the required attributes for use in an artificial personality. This measurement was both simple in that it can easily be calculated and used, but it is also simple in that it is clear how expression can be transmitted through the channel—it can map neatly onto human emotions (see Fig. 2). The success of the channel in the full system evaluation (including the fact that perception of the responsiveness of the system was impaired when noise was introduced) also means that it is successful as both an expressive and embodied channel.

The indirectness measurement (see Eq. 3) was less successful than the power measurement. While simple to calculate, the measurement did not map neatly onto human expression or emotions. However, when the robot generated movements within its more limited movement vocabulary, they were distinguishable to our eyes.

The pointing or following behaviour of the robot (based on the kinesphere LMA subcategory) showed some potential. This is simple to implement, is tractable, and maps neatly onto behaviour. The expressive quality of this communication channel relates to attention. The robot can use its physical location to pay attention to the dancer, or to move away to dance in a different space. It was difficult to implement in the full system due to the inaccuracies in our measuring systems.

As far as the production of artificial personalities is concerned, there is potential to build more sophisticated models into the robot's Improvisation subsystem. This could allow us to experiment more closely with different personality models and explore the system as a tool for analysis of human interaction. The development of a methodological approach for studying this in more detail is an exciting project.

Insights into emergent communication channels can also be gained from studying the communication channels we have outlined. Put simply, the power measurement measures the amount of energy being expended by an agent during its movement. Observers can quickly make judgements as to an agent's internal state based on this measurement and any other measurement that measures energy usage (e.g., sound volume, metabolic output, etc). It should be noted that it is also difficult for an agent to hide or fake its energy consumption so this forms the basis of a communication channel that is unintentional and emergent and therefore likely to be an early channel to evolve. Looking for other, unintentional, movement channels may well be productive.

Acknowledgements

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