13

Robotic Dancing, Emotional Gestures and Prosody: A Framework for Gestures of Three Robotic Platforms

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13.1 Introduction

Robots have the potential to be effective music-interpretive dancers that entertain, foster trust, and provide new ways to interact with humans. A robot's movement (including dance) can change the way a person perceives and interacts with a robot [31]. In many cultures, music and dance co-evolved and serve as important elements in social behavior [23]. This is because humans relate to both music and dance on physical and psychological levels. Music not only induces movement in people [18,37] but also can elicit empathy. According to Leman, this empathy is the necessary connection between the emotions hidden in music and the expression in body movements [46].

When a listener feels an emotion in music, they often reflect that emotion in their gestures. Similarly, a good dancer understands how to portray emotions in their movements, and therefore, is able to reflect the emotions from music in their movements. Taking this one step further, we hoped to create a robot dancer that can give people a way to experience emotion, as well as using this shared emotion to help establish a positive connections with robots in general, especially non-anthropomorphic ones. This chapter explores two fundamental issues, firstly how can emotional gestures be portrayed across different robot platforms while incorporating sound. The second issues address re-purposing the developed gesture framework for longer form dance to music.

We first developed a comparative approach for depicting robotic emotions using sound and gesture in three different platforms: Stretch by Hello Robot[1], Panda by Franka Emica [2], and SeekerBot, an internally developed social robot. These robotic platforms represent unique current trends in robotics, and each comes with its own Degrees of freedom (DoF), size, design, and utility. Stretch is a human size mobile manipulator with a wheel base and a telescoping arm; Panda, is a 7 DoF robotic arm designed to function as an industrial arm or cobot. The SeekerBot is a 2 DoF tabletop social robot with a LED display for a face. Based on the similarities to human morphology, posture recreation and manipulation, we regarded the SeekerBot as the most anthropomorphic platform in our study, followed by the Panda. While the Stretch is a human size mobile robot, it's morphology, speed, and non-humanoid telescopic arm, rendered it as the least anthropomorphic platform. We believed that each

[1] https://hello-robot.com/product
[2] https://www.franka.de/robot-system

of these platforms represent an important category in robotic design, which can help provide a comprehensive comparative evaluation of robotic emotion depiction through sound and gesture.

To conduct our study, we used an interactive design methodology based on [84], [58], and tested the perception of emotion for each gesture in a user study. We generalized this methodology to map human gestures to robots of similar physiology. We used emotional musical prosody to generate sounds, as described in Chapters 10 and 11. We evaluated the impact of our emotional gesture and prosody generators across the three robotic platforms for animacy, anthropomorphism, likeability, and perceived intelligence. The contribution of this research is a comprehensive evaluation of the manner in which different robotic platforms and approaches for gesture generation alter common HRI metrics and the portrayal of emotion, and a guideline for mapping human gestures to non-humanoid robots. This guide can help future robotic platforms incorporate emotional movements in their trajectory/movement planning for various non-humanoid robots.

The second research area of this chapter, uses this framework to create robotic dance based on musical features from a song. A seven degree of freedom (7DoF) robotic arm was used as the non-humanoid robot. The gestures, or dance movements, were designed to respond to music in a way that corresponds to a human's perception of an expressed emotion. As a result, the robot will appear to be improvising and designing it's own dance based on the music. The robot can be used as another bridge between music and dance. We leveraged Burger's research on correlations between different musical elements and various body motions [18] to create a mapping between musical features and a single robot's gestures as well as accompanying gestures of additional robots. Video samples of all gestures can be viewed at www.soundandrobotics.com/ch13

13.2 Related Work

13.2.1 Emotional Gestures in Robotics

Conveying emotions in robotic behaviors is an important tool for facilitating social interactions with humans [6]. Robotic researchers have been using a wide variety of modalities to convey emotions in robots including speech [14, 47], sound [24, 77], body posture [29, 80], facial expression [11, 13] [19], and body gestures [36, 54, 67]. These projects have commonly utilized either discrete [5, 66], continuous [53, 56] or integrative approaches [70] for emotion classification. Emotion conveyance in robots has been helpful in improving the perception of robots by human subjects in human–robot interaction scenarios. Bartneck [13] has shown that emotional facial expression in the social robot iCat significantly increased its likeability and anthropomorphism. Monceaux showed how emotion-driven robotic posture on the robot NAO enhanced its perception of animacy [54].

Gestures are often used to signal communication and display meaning or ideas [51]. A common approach of gesture design simulates human motion [20]. Cha discusses the challenges of mimicing human motion with non-humanoid robots and suggests an approach to increase animation of robots. Motion re-targeting looks at emulating a series of human postures. Kaushik looked at the skeletal model of a human and digitally reduced the profile to smaller non-anthropomorphic agents. Kaushik's research showed reduction of human movements, but did not focus on emotions [41]. In emotional gestures, motion re-targeting can be used to adapt human body gestures to robotic joints. Novikova and Watts created five flowcharts mapping emotional gestural expressions for a lego mindstorm non-anthropomorphic robot [59].

A few researchers such as Read, Dautenhahn, and Braeazeal [63] [25] [15] focused on sound generation as a tool to help convey emotions in robots such as Aibo, PeopleBot, and Kismet. Read [63], for example, has shown how embedding prosody over robotic speech can help its perception of intelligence. Embedding emotions in robots has also been shown to contribute to improving robotic performance in tasks such as museum tours, assistance for the elderly, and healthcare. Vasquez [83] has shown that using emotions in their guide robot Doris improved it's effectiveness and entertainment as a guide, while Ferreira [48] has shown that the NAO robot can reduce loneliness with the inclusion of emotions.

One of the most prominent current challenges in robotic research is establishing trust in human–robot interaction. Researchers have explored multiple approaches to enhance trust including emotion conveyance through gesture and sound. Araiz-Bekket showed that unpredictable robot movements lowers a human's trust in them and also increases that persons discomfort [1]. Other prior work showed gestures and music improved trust with Shimi robot [69]. Additionally, it has been shown that musical prosody improved trust when interacting with a virtual robotic arm [71]. While conveying emotions in robots has proven to be useful for a wide variety of purposes, no comparative and integrative research has been done to our knowledge, that embed both sound and gesture generation in multiple robotic platforms to generate and assess emotions and their effect on subjects.

13.2.2 Robotic Dance Generation

There are different approaches to automatic dance generation in robots. Alemi and Pasquier listed a survey of machine learning techniques that generate human motion based on various features of human motion [4]. This was similar to their work on GrooveNet, a real time animation of humans dancing to music [3]. Joshi and Chakrabarty created a notation style to analyze and generate dance trajectories. Similar systems of feature extraction and notation can be used for robotic dancers [39]. Another, possibly more popular approach, to robot dancing is manual coding. Boston Dynamics released videos of their humanoid robots dancing to various songs [33]. Merrit Moore also released a set of dances with a robotic arm (7 degree of freedom) [3]. Both of these projects involve manually programming the robot's dance moves. Alternatively, Shimon and Shimi use the beat of the music to bob their head and follow different musicians [16,73]. Xia and Shiratori used multiple musical qualities to generate dances for a humanoid robot [75,86]. This work is expanded in a variety of humanoid robots using primarily the music and rhythmic as input. Most of the systems sync the robot trajectories with a beat gathered from music [52,60,61,65,68,78].

Other attempts at robotic dance look to adapt their trajectories based on human motion. Augello and Jochem explored different machine learning approaches to humanoid dancing [8,38]. Both Hagendoorn's and Wallis' work center around human-inspired dance for humanoid robots [35,85]. LaViers and Alcubilla looked at rule-based systems that are inspired from dance theory. Alcubilla created a mapping from Laban Movement analysis, and expanded Forsythe's tools for improvisation on robots [2].

13.3 Approach

We created two research questions to guide the design and improve movement for non-humanoid robot dancers:

RQ 1 In what ways can a non-humanoid robot express the emotion of human gestures?

RQ 2 In what ways can a non-humanoid robot express emotion and fluency of human gestures as a dance response to music?

We designed emotion-driven gestures and in combination with emotional musical prosody (EMP) for three robotic platforms: a social robot (Seekerbot), a collaborative robotic arm (Panda), and a mobile manipulator (Stretch). To generate EMP we used the same process described in Chapters 10 and 11. Emotional musical prosody (EMP) was used instead of speech as it better matches the morphology of a range of robots and has shown significant results for improving trust and likeability [72]. EMP consisted of short, emotionally tagged musical phrases designed to convey meaning to human collaborators using non verbals means.

[3]https://www.universal-robots.com/blog/dancing-through-the-pandemic-how-a-quantum-physicist-taught-a-cobot-to-dance/

13.4 Gesture and Emotional Musical Prosody Generation

Research question 1 started with the development of robotic movement inspired by human emotion. We first developed a framework for designing gestures that can appear emotional based on our generated emotional musical prosody phrases.

13.4.1 Gesture Design and Generation

Our gesture design approach for each robotic platform considered the similarities and differences in affordances in relation to a human's physical methods of conveying emotions. To generate emotion gestures, we related motions from each robots degrees of freedom to similar human gestures. The robotic gestures were designed in an effort to mimic emotional human gestures as described by [22, 40, 58, 74, 81, 84]. Tables 1-3 present an overview of our design approach for mapping emotional human gestures to the DoFs available in the three robotic platforms. Column 3 in the table presents a the human gesture for an emotion described in Column 2. Each emotional gesture guideline was generalized to address the focused movement directions for non-humanoid robots, as presented in Column 4. Columns 5 generalizes the speed interpretation. While the guideline tables do not suggest specific mapping instructions, they are designed as a reference for other researchers looking to create emotional gestures. Each table is intended to be general enough so that it could be applied to a wide range of non-anthropomorphic robots. These tables are designed to act as a baseline which could be used to create more specific rules to create emotional gestures for different robotic platforms.

13.4.1.1 Stretch Robot

The mobile manipulator robot Stretch provides a unique combination of movements and DoFs with its telescopic arm that can move up and down, camera movement with tilt-pan mount, and spatial movement through two wheels as seen in Figure 13.1. The robot's emotional gestures were designed by Mohammad Jafari based on the guideline tables. This was done by matching each of the robot's DoF to a combination of human joints. The gripper mechanism was mapped to all human arm movements. The camera was mapped to the human head, rotating upward and downward for positive and negative emotions respectively. The camera also panned to simulate human eye contact and avoidance. Since leaning can symbolize the distance from the stimulus, we decided to map these gestures to the Stretch's wheel base. Raising and lowering the robotic arm represented erect and collapsed shoulder positions.

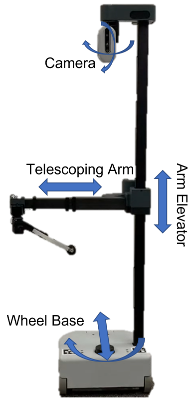

FIGURE 13.1
Model of the stretch robot.

13.4.1.2 Panda

The co-bot Panda arm we used has seven DoFs, allowing it to rotate in unique ways that can support human motion recreation and improved object manipulation. While the Panda is not a humanoid robot, it's degrees of freedom can be used to create various postures and gestures. Figure 13.2 shows the joint labels and movements. Gestures were created by assigning each joint specific angular movements with various velocities. To convey emotions, we matched the robot's DoFs to a profile of human posture and gesture as can be seen in Figure 13.3. Each gesture was mapped to a series of robot poses to match these profiles. The time it would take to switch between poses was determined by velocities indicated in the guideline table.

In general, joint 4 was used for posture changes, joint 2 for leaning positions. Joint 1 focused on adding sideways motions such as shaking body for fear or avoidance for shame. Since joint 6 moves the end effector of the robot, it was mapped to human head motions and would rotate to tuck one's head in/out. Joint 5 also acted as side movement for head shaking or any extra motions that would be needed for additional expression of a gesture. For example, an erect posture commonly used in joyous gestures were mapped to move joints 2 and 4 to 30 and 150 degrees. This actuated the robot to move from slightly to fully erect position. The up and down movement simulated jumping up and down or moving hands up and down; both common human gestures for joy. Forward leaning posture in emotions such as anger and love had joint 2 positioned at 210 degrees. A collapsed position, seen in sadness, set joint 4 to 215 degrees and joint 6 tucked in.

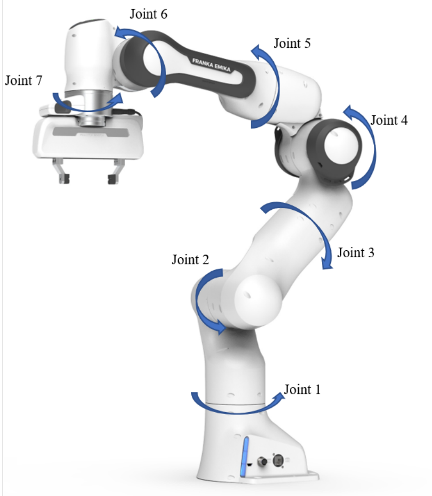

FIGURE 13.2
Panda robot with labeled joints and movements.

13.4.1.3 SeekerBot

The SeekerBot (see Figure 13.4) is a biped robot designed and built in-house by Rishikesh Daoo to portray emotions through gestures and facial expressions. The design of the robot is based on OttoBot [4], an open source platform for free education in the field of robotics. Gestures are designed by Rishikesh Daoo and used as comparison to the other robotic platforms.

Given the limited mechanical abilities of the SeekerBot, most mappings focused around expressions from the LEDs and leg movements. The legs were used for side to side motion of human bodies or head. The robot's second actuator could move itself toward and away from a stimulus. Human motions that had higher movements such as anger would be linked to the legs, as well as any forward or backward leaning posturing.Supplemental gestures were embellished with movements of the LED screen to mimic basic facial movements observed by studied works.

[4] https://www.ottodiy.com/

FIGURE 13.3
Example of robotic arm creating a linear profile of Dael's [58] fear position.

FIGURE 13.4
The SeekerBot.

Co-Bot Arm (Panda)				
DoF	**Human Movement**	**Emotion**	**Position Adaptation**	**Speed Adaptation**
6	Head bent down [22]	Sadness, Shame	Joint tilts end of robot downwards	Slow
	Head bent up [22]	Joy	Joint tilts end of robot upwards	Fast
	Up-down repetitive arm motion [58]	Pride	joint tilts end of robot upward (rest of joints give up and down appearance)	Fast
	Backwards shoulders [84]	Disgust	Joint tilts end of robot away from stimulus	Fast
5	High arm movement [58]	Fear	Twists front part of robot moving head in and out of body	Fast
	Looking away from the interactor (toward the right) [40]	Guilt	Rotates top half of robot to avoid stimulus	Slow
	Higher knee movement [58]	Pride	Joint rotates top half of robot side to side	Slow
4	"Collapsed Upper Body" [58]	Sadness	Joint collapses top half of robot toward itself	Slow
	Opening/Closing many self manipulators [7]	Fear	Collapses robot in on itself	Fast
	Collapsed position [40]	Guilt	Collapses top half of robot down	Slow
	Up-down repetitive arm motion [58]	Joy	Raises and lowers top half of robot	Fast
	Collapsed Shoulders [84]	Shame	Collapses top half of robot down	Slow
	High arm movement [81]	Pride	Joint moves top half of robot up and down	Medium
	Arms at rest [84]	Relief	Joint collapses top half of robot into itself	Fast to slow
3	Looking away from the interactor (toward the right) [40]	Guilt	Rotates top half of robot to avoid stimulus	Slow
	Higher knee movement [58]	Pride	Joint rotates top half of robot side to side	Slow
2	Weight transfer backwards [74]	Fear	Leans whole robot back	Fast
	Backwards leaning [40]	Shame	Leans robot away from stimulus	Slow
	Weight transfer backwards [22]	Disgust	Leans robot away from stimulus	Fast

Mobile Manipulator (Stretch)				
DoF	**Human Movement**	**Emotion**	**Position Adaptation**	**Speed Adapation**
Camera	Head Bent Down [22]	Sadness	Camera looks at floor	Slow
	Looking away from the interactor (toward the right) [40]	Guilt	Camera tilts up then pans side to side	Medium speed
	Head bent up [22]	Joy	Camera tilts up	Medium speed
	Head facing down [22]	Shame	Camera tilts down	Slow
	Arms at rest [32]	Relief	Camera tilts up	Slow
Telescoping Manipulator	Low Movement Dynamics [74]	Sadness	Gripper telescopes inward	Slow
	High arm movement [74]	Fear	Gripper telescopes inward	Fast
	High arm movement [81]	Pride	Gripper telescopes slightly	Slow
Manipulating Elevator	Smooth falling hands [84]	Sadness	Arm slides down to floor	Slow
	High arm movement [58]	Fear	Arm slides upward	Fast
	Collapsed Shoulders [40]	Shame	Arm slides down to floor	Slow
	Up-down repetative arm motion [58]	Pride	Arms slides up and down	Slow
	Arms at rest [84]	Relief	Arm slides down a bit	Slow
	High shoulder swings [22]	Disgust	Arm slides up and down	Fast
Wheel Base	Weight transfer backwards [58]	Fear	Wheels drive robot away from stimulus	Fast
	Looking away from the interactor [40]	Guilt	Wheels rotate robot away from stimulus	Medium speed
	Backwards leaning [40]	Shame	Wheels rotate robot away from stimulus	Slow
	Higher knee movement [58]	Pride	Wheels move toward stimulus	Slow
	Weight transfer backwards [22]	Disgust	Drives away from stimulus then rotates side to side	Fast

Social Robot (Seekerbot)				
DoF	**Human Movement**	**Emotion**	**Position Adaptation**	**Speed Adaptation**
Eyes	Head bent down [22]	Sadness	Eyes look down at floor	
	Opening/Closing many self manipulators [7]	Fear	Eyes open wide	Fast
	Brows lowered [40]	Guilt	Eyes look down at floor	Slow
	Cheek Raiser [21]	Joy	Eyes squint	Fast
	Head looking down [84]	Shame	Eyes look down	Slow
	Closed Eyes [81]	Pride	Narrow Eyes	Slow
	Brows are lowered [34]	Disgust	Eyes narrow toward each other	Fast
Eyelids	Inner corners of eyebrows are drawn up [34]	Sadness	Inner corners of eyebrows move upwards	Slow
	Brows are lowered [40]	Guilt	Eyelids squint inwards	Slow
Eyebrows	Inner corners of eyebrows are drawn up [34]	Sadness	Inner corners of eyebrows move upwards	Slow
	Raising of inner brows [28]	Shame	Inner corners of eyebrows move upwards	Slow
	Brows are lowered [34]	Disgust	Eyebrows squint inward	Fast
Mouth	Corners of the lips are drawn downwards [34]	Sadness	Mouth Frowns	Slow
	Fear	Fear		
	Frowning, lips stretched [40]	Guilt	Frowning	Slow
	corners of lips are drawn back and up [27, 84]	Joy	Mouth smiles widely	Sudden Change
	Small [81]	Pride	Mouth smiles	Slow
	Lower lip is raised and pushed up to upper lip [34]	Disgust	Mouth frowns	

Social Robot Cont'd				
Legs	Collapsed Upper Body [58]	Sadness	Legs bend to collapse robot	Slow
	Weight transfer backwards [22]	Fear	Robot moves away from stimulus	Fast
	Looking away from the interactor (toward the right) [40]	Guilt	Legs move robot away from stimulus	Slow
	Body action: Jumping, Shape change: Expansion [74]	Joy	Legs tilt robot side to side	Rapid speed changes
	Collapsed Shoulders [84]	Shame	Legs tilt robot	Slow
	Fully visible, expanded posture [81]	Pride	Legs stand robot up and slightly tilts side to side	Slow
	Shoulders lean down [32]	Relief	Legs tilt robot side to side	Slow
	Backwards shoulders [84]	Disgust	Legs move robot away from stimulus	Fast

13.4.2 User Study

After developing a new framework for gesture creation we conducted a study to validate how humans perceive both gestural and EMP on each one of the robotic platforms. We further break down the research question into sub-questions to evaluate the system:

RQ1A *Can non-anthropomorphic robots of various structures express emotions within each emotion quadrant through gestures and emotional musical prosody?*

We hypothesize that for each platform, people will be able to interpret the simulated robotic emotions. The ability for humans to recognize emotions of other humans has been measured to be around 72% [10, 64], giving us a baseline recognition goal. We also hypothesize that the more anthropomorphic a robot is, the better it will perform in depiction of emotions .

RQ1B *How does the use of emotional musical prosody influence the recognition of emotional gestures on all platforms?*

Our hypothesis is that when combined across platforms the emotion driven prosodic voice will significantly outperform robotic performance with no audio. We also hypothesize that adding voice will increase variation between the platforms.

RQ1C *How will embedding emotional musical prosody and gesture design alter the perception of anthropomorphism, animacy, likeability perceived intelligence for different robotic platforms ?*

We expected to have no significant results for this research question as we were comparing six conditions (three robots, each with two audio types) using a between group study design. We thus posed the third question as an exploratory comparison using the widely used Godspeed metrics [12].

13.4.3 Experiments

We designed a between subjects experiment for participants to validate emotions on each robotic platform. The first part of the experiment aimed to address Research Questions 1-2. The second part analyzed the Godspeed metrics for Animacy, Anthropomorphism, Likeability and Perceived Intelligence.

As part of the experiment we asked participants to identify the emotion of different stimuli based on the GEW. We chose the GEW to match the models used for our EMP generation and validation method. The GEW provides both discreet and continuous selection of emotions. The stimuli consisted of combinations of robot EMP or no audio with each platform for a total of 9 different sets of stimuli. The stimuli consisted of the robotic platform displaying an emotion in sync with audio using the same gestures used for each group.

Due to social distancing requirements, we used videos of all three robots in front of a white background as our stimuli. Studies have shown that levels of a robot's presence affects some variables in human–robot interactions [9,79]. We believe having all the robotic platforms at the same level of presence, through videos, would mitigate this effect.

After completing a consent form, participants were introduced to the GEW and were given a test question to teach them the layout of a GEW. The test question required selecting a specific emotion without which participants were not allowed to continued. Participants were then shown one of the stimuli with audio, such as Stretch with robot EMP or SeekerBot with no EMP. This was followed by completing the Godspeed test. Participants then viewed and rated on the GEW a second set of stimuli of a different platform without audio. No part of the stimuli was repeated for any participant. The average study length was 12 minutes.

For the experiment, 150 participants were recruited, with 11 rejected for incorrect answers on attention checks, leaving a total of 139 participants. From the participants used in the study 89 identified as male, while the other 50 identified as female. 101 were currently in the United States, 30 in India, with the remaining 8 spread between Ireland, Brazil, and Thailand. For both studies the mean age was 41 with a standard deviation of 11 and a range of 18–77. We found no statistically significant difference between demographics. The study was 15 minutes long and paid USD$2.00 per study. The study was approved by the university Institutional Review Board.

13.5 Results

13.5.1 RQ1A: Emotion Validation

We found high ratings for accuracy for emotion detection in three of the four quadrants for gestures and audio. For the Panda arm and SeekerBot participants consistently score over 85% accuracy, achieving higher accuracy than the 72% achieved by humans recognizing other human faces. For the high valence / low arousal quadrant emotion detection accuracy was significantly lower. However participants still scored consistently above random. Across the majority of categories the Stretch performed worse than the other two robots. Figure 13.5 shows the percentage of accurate results for EMP and gesture combined.

We first conducted a one-way Anova comparing between the three robots, with the results *(p <0.001, f = 14.335)*. A summary of related statistics is presented in Table 13.1. We then conducted a post-hoc test, using Tukey Honestly Significant Difference. We found significant difference in how clearly the emotions were perceived between Arm and the Stretch and the Arm and the Seekerbot, implying the audio and gesture design was more effective on these platforms.

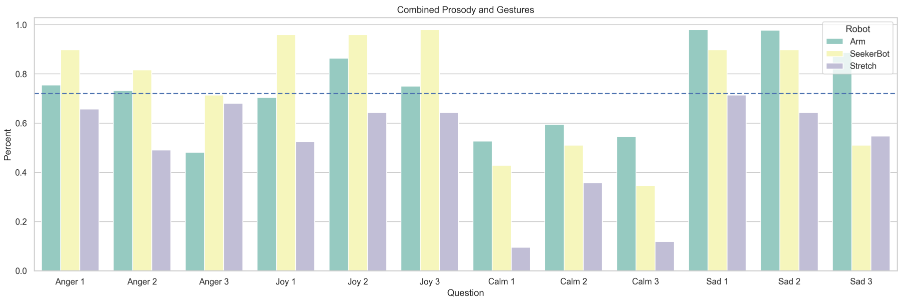

FIGURE 13.5
Combined EMP and gesture emotion recognition (dashed line indicates 72%).

TABLE 13.1
One-way ANOVA statistic summary.

Robot	N	Mean	SD	SE	95% Conf.	Interval
Arm	36	0.7326	0.1668	0.0278	0.6762	0.7890
SeekerBot	36	0.7426	0.2248	0.0375	0.6665	0.8187
Stretch	36	0.5163	0.2116	0.0353	0.4447	0.5879

13.5.2 RQ1B: EMP and Gesture Comparison

We found no significant results between EMP and gesture for the SeekerBot or the Panda arm ($p > 0.05$). For the Stretch, EMP improved the recognition of emotion across all 12 questions. A pair-wise t-test for EMP and gesture returned $p = 0.035$, $f = 0.04$, indicating a significant result. Figure 13.6 shows the accuracy for gesture alone, and Figure 13.7 show the results for EMP. Figure 13.8 shows a box-plot comparing between platforms.

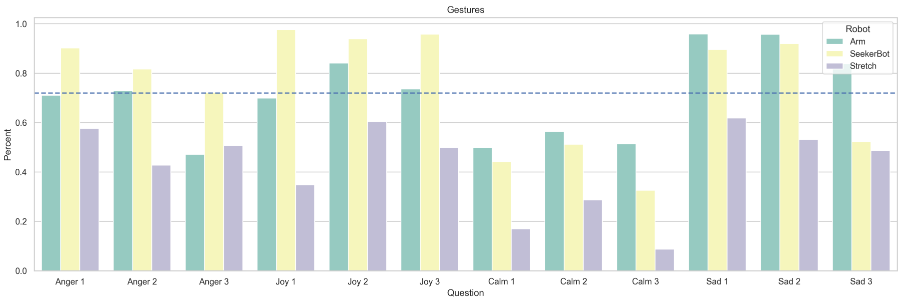

FIGURE 13.6
Gesture emotion recognition (dashed line indicates 72%).

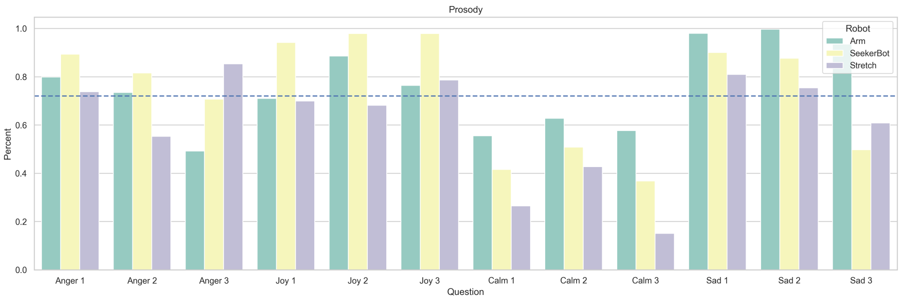

FIGURE 13.7
EMP emotion recognition (dashed line indicates 72%).

13.5.3 RQ1C: HRI Metrics

We first calculated Cronbach's alpha for each question, with each metric over >0.85, indicating high internal reliability. After Holm–Bonferroni correction we found no significance between any audio and gesture comparison. Nevertheless, between platforms there was wide variability while EMP did consistently score higher than gesture alone.

13.6 Discussion

13.6.1 Emotion Recognition

For every quadrant except for Calm (low valance / low arousal), participants correctly identified the quadrant. The SeekerBot performed best for quadrants 1 and 3 (Joy and Anger), while the Panda arm had the best recognition for quadrants 2 and 4 (Calm and Sadness). The Stretch performed significantly worse in all quadrants; matching our hypothesis. The Seekerbot and Panda arm received closer ratings than the Panda arm and Stretch. We theorize that this can be explained by the fact that the SeekerBot and Panda arm have a similar number of degrees of freedom. Anger and Joy quadrants contain emotions that are highly correlated to facial movements. The Seekerbot, being the only robot with facial display, improved its expression in those quadrants.

The fourth quadrant (Calm) had the least accurate emotion identification results. While EMP helped improve emotion identification even in this quadrant, all three robotic adaptations struggled to effectively express their emotions. One possible explanation may be due to the lesser amount of gestures specifically related to emotions of this quadrant.Emotions in the fourth quadrant such as love and relief can have more personal interpenetrations, which might indicate that other researchers had similar trouble correlating specific gestures and rules for emotions within the fourth quadrant.

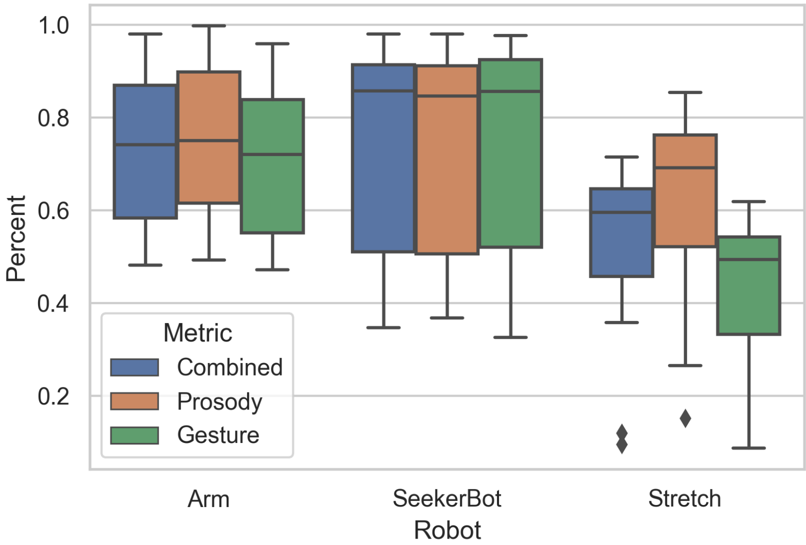

FIGURE 13.8
Comparison between accuracy for EMP and gesture on each platform.

13.6.2 Emotional Musical Prosody

While insignificant when tested across all gestures, there was a slight improvement with the Panda arm when EMP was added. The Panda performed worse than SeekerBot for no audio but was not significantly different from the SeekerBot for either EMP group. Because some gestures performed worse than others, as evidenced by Figure 13.9 we speculate that EMP was helpful for detecting emotions that are more difficult to identify from gestures alone. The accuracy for SeekerBot did not improve when EMP was added. This might imply that its face, which the other robots lacked, provided enough information that significant improvement was not achievable.

The Stretch robot was the only platform that showed significant improvement in emotion detection when EMP was added. One possible explanation for this could be that the Stretch design has the least emotion conveying anthropomorphic affordances, leading to more challenges in producing subtle differences between emotions. Our gesture design guidelines generalize the movements for each emotion, where subtleties between emotions can be more easily tuned with more degrees of freedom. However, without enough degrees of freedom, some emotions may have appeared too similar to each other. We hypothesize that the addition of EMP to robots that are otherwise less anthropomorphic and expressive, such as the Stretch, can improve and enrich subtleties in emotion conveyance.

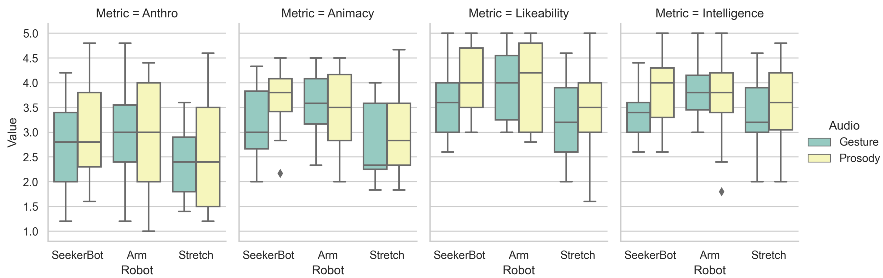

FIGURE 13.9
Godspeed metrics between platforms.

13.6.3 Godspeed Metrics

For every category except perceived intelligence, the Panda arm performed the best. While understanding motivation for godspeed metrics can be challenged, we believe that The Panda performed best due to the increased variety in degrees of freedom. The Panda Arm has 7 high ranged Degrees of freedom (more than any other the other bots). We suggest that this allows for increased variety of expression and can enable a robot to more accurately simulate a specific gesture. Increased expressivity would correlate well with a perception of animacy, where a robot with the least degrees of freedom had the lowest ratings out of the three. The difference in degrees of freedom between SeekerBot and the Panda arm are small, and therefore, they received similar ratings. We theorize that the Panda arm has more variety in its uses of each degree of freedom where some of the SeekerBot movements are more limited.

13.6.4 Limitations

In order to comply with social distancing, all studies were conducted online. This limited our opportunity to evaluate the effects of physical interactions with each robot. Future work could look at how the sizes of each robot can affect the users perception. While using the GEW as our emotion model gave users a variety of options to choose from, we suspect it gave the participants a potentially overwhelming amount of options. For example, some participants could have choosen the term pleasure instead of joy. While these terms are next to each other in the GEW it shows that their recognition was accurate, but not exact.

After the development of new movements, we looked to apply them to more intricate dances. We combined these gestures to create a series of dance steps, that we then combined to make complete dances.

13.7 Applying Gesture Design to Dance

To create a robot dancing meaningfully to music, we started off by taking the framework for gesture designs developed in RQ1 and played them in a musical context. We achieved this by referencing a variety of literary sources relating musical features to human body movement. We mapped human movements to similar robot movements (as done in RQ1 for emotion) that we generated based on the rhythm, energy, and pitch. For example, an increase in lower frequency spectral flux results in an increase in head movements. We used this as a basis for programming a robotic arm to react in specific ways to music. We created dances in three systems:

- Pick a dance that best matches the music playing
- Generate new dances in real-time
- A combination of both systems

A successful system would show an improvement in the Performance Competence Evaluation Measure [43], and HRI godspeed metric. In addition, a successful system would show an observer that the robots can improvise and react artistically to music. We first developed a system to pick a dance from a gesture database. After we performed basic evaluations, we use this feedback to help improve the development of the next system. After performing another set of evaluations, we combined both systems and conducted a final study to compare all the three systems.

13.7.1 System 1: Dance Selection Based on Music

We used Burger's work mapping human movement to musical features to develop a mappings table that links musical features to human and robot movements. The robot movements were mapped based on our emotional gesture mappings in Research Question 1 and a literary review of publications relating musical features to movement [17,26,30,49,50,57,62,76,82]. Table 13.2 shows the correlations between musical features and human body movements.

We used a set of music information retrieval libraries to extract song information. We used Madmom's recursive neural net to detect onset and rhythmic information, Numpy to detect frequency features as well as RMS, and Msaf to section the piece. Librosa performed source separation for instrument changes. The Msaf library determined the sections for each piece. We chose these libraries for their accuracy throughout a variety of songs and genres.

TABLE 13.2
Table showing mappings of musical features with human and robotic motion.

Musical Feature	Human Movement	Robot equivalent Movement	Relationship
Low frequency spectral flux	Head Movement [17,45]	Joint 5, 6	Speed of movement increases with higher flux
High frequency spectral flux	Head Movement [17]	Joint 2, 4	Speed of movement increases with higher flux
	Hand Movement [17,26]	Joint 3, 4, 5	Hand distance and amount of movement increases with higher flux
Onset strength	Center of Mass [62]	Joint 2 and 4	Speed and distance travel increases with higher onset strength
	Shoulder movement [17]	Joint 4	Speed of motion and amount of shoulder wiggle increases with higher onset strength
Percusiveness (envelope slope)	Center of mass [50,62]	Joint 2, 4	Speed of body motion and distance increases with more percusiveness
	Shoulder [17,82]	Joint 4, 5	Speed of motion and amount of shoulder wiggle increases with higher percusiveness
	Hand movement [17,76,82]	Joint 3, 4, 5	Hand distance and amount of movement increases with higher percusiveness
	Head movement [17,62]	Joint 5, 6	Speed of movement and amount of head bobs increases
Energy (RMS)	Head movement [62]	Joint 5, 6	Distance of movement increases with higher RMS
	Body movement [62]	Joint 2, 3, 4	Distance of movement increases with higher RMS

13.7.2 Musical Feature Recognition

The musical features were detected using a variety of machine learning algorithms. To analyze the musical features (for any system), a song was first blocked, and FFT's were performed. The audio information was sent to each respective library to determine sections and rhythmic information. We proceeded to generate values for all desired musical features every five milliseconds. We then normalized these values and calculate the differential of each musical feature. Each gesture was selected based on the values for each section.

Music analysis was performed offline before generating a dance to get more accurate data than real-time music information retrieval. After we analyze a song once, we can generate multiple dances with (the same or) different systems quickly in real time. Analyzing music offline gave us the opportunity to look ahead of the song and time section changes accordingly with robot dances.

13.7.3 Robot Gesture Database

A dance is composed of a series of gestures, which can be further broken down into joint movements. To create a gesture, we combined joint movements that can be designed by inputting the change in degrees of each joint, the time to start this motion, and the time to finish this joint movement. Each robot gesture was then scaled based on the calculated BPM of a song. A script was designed to convert desired joint movements into smooth robot trajectory plots that also included follow through.

We used the emotional gestures developed in RQ1 as well as a variety of dance gestures that had been derived from the emotional gestures by members of the music-technology department at Georgia Tech. Such gestures were used in previous performances and developed by dancers. Each dance had a starting position, number of robots involved, duration, and max speed. When a dance is selected, the gesture speed was modified to match the calculated BPM of the song. The trajectory of each dance used a 5th order polynomial (as determined in RQ1) and included follow through. Dances were sorted based on their max speed, maximum movement of each joint, and amount of robot total movement (total displacement of movement in each joint).

13.7.4 Decision Tree for Dance Selection

Dance selection was performed iteratively over each section of the input song. We first looked at the total duration. If a section was longer than our longest gesture in the database, we selected an additional robot gestures to increase diversity of the dance. We then looked at the following analyses for each musical feature: Average value, maximum change in value, range of value, time difference between max change.

We then selected a robot gesture from the gesture database that was most similar to the values of music features. We did this by going through each musical features and selecting a group that best matches the features. For example, the section with the highest RMS selects one third of the gestures with the biggest amplitude changes in joints. We then checked the next musical feature and took one third of this new group based on the features values. The decision tree below (Figure 13.10) shows the process for selecting gestures in a piece.

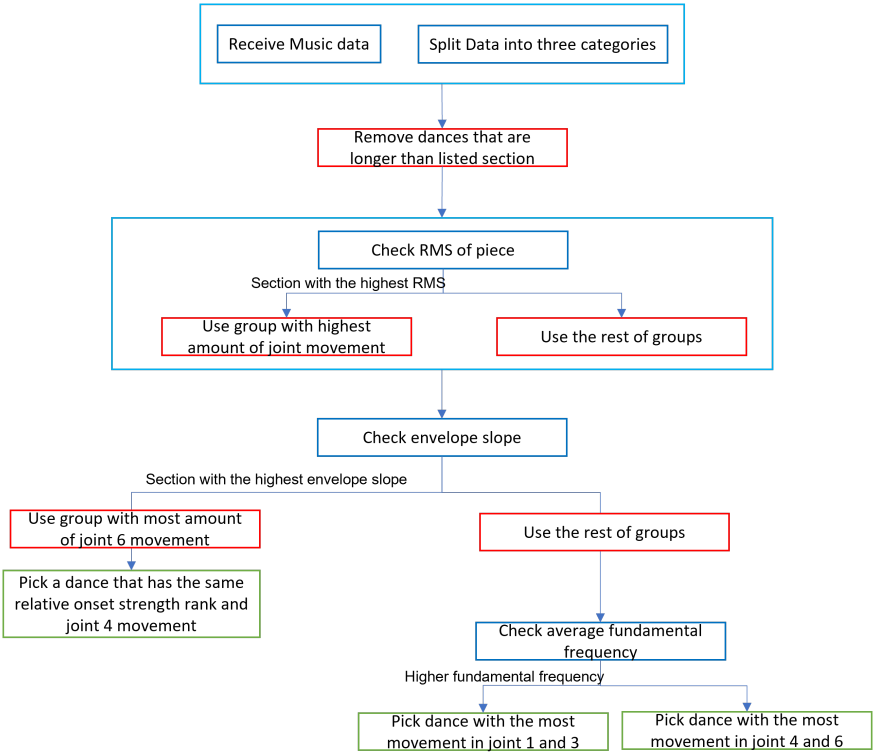

FIGURE 13.10
Flowchart of selecting a dance to best match the musical features.

Every iteration of a section took a third of the dance gestures from the database that best matched the music feature desired. We prioritized features with the most correlations to human movement as the first set of filtering. This ensured that the strongest links between movement and music are most accurately depicted in the selected gesture. We repeated this process for each of the sections in a song.

13.8 System 2: Dance Generation Based on Music

13.8.1 Generate New Dances in Real-time

The original inspiration of linking music to movement started with human movements that are inspired by music. However, these correlations did not guarantee mappings that audience members can easily identify. Using qualitative feedback received from informal interviews, we improved the choice of musical features and and created a system that generated and manipulated live trajectories for each section of a song. We modified the robot section of all mappings to focus on the frequency and amplitude of continuous movements, rather than discreet motions.

13.8.2 Mapping Musical Features to Robot Movement

We first looked to improve our dance generator by modifying the mappings from musical features to robot movements. Krumhan's work showed that humans can best correlate simple musical features to body movements [44]. In our new dance generation system, we chose to only use RMS, tempo, and song section as they were the most recognizable features for non-musicians [42]. For trajectory design, we set joint angles to follow a sine wave that changed in amplitude and frequency based on musical features. The robotic arm had a set of unique poses that it could go to after each section. Then, a weighted probability table determined which joint would start moving next, at a given amplitude and frequency based on a musical feature. The robots design allows different aesthetics based on which joint is moving. The joint moved was chosen based on the fundamental frequency; where a lower fundamental frequencies would move a joint closer to the head joint 5 and 6. RMS value increased the amplitude of a joints movement and the frequency of the sine wave was determined by the tempo.

13.9 System 3: Combination of System 1 and 2

13.9.1 Dance Generation

A third system of dance generation was created in an attempt to combine the positive feedback from both dance generators. This version utilized the whole group of robots by having a number of robots play visually aesthetic gestures(from system 1), and having at least one robot moving with simple mappings from system 2. Each section used the average RMS to determine how many robots would play choreographed gestures, and how many were expressing musical features. Based on the layout and number of robots selected, there were set patterns for which specific robot to play.

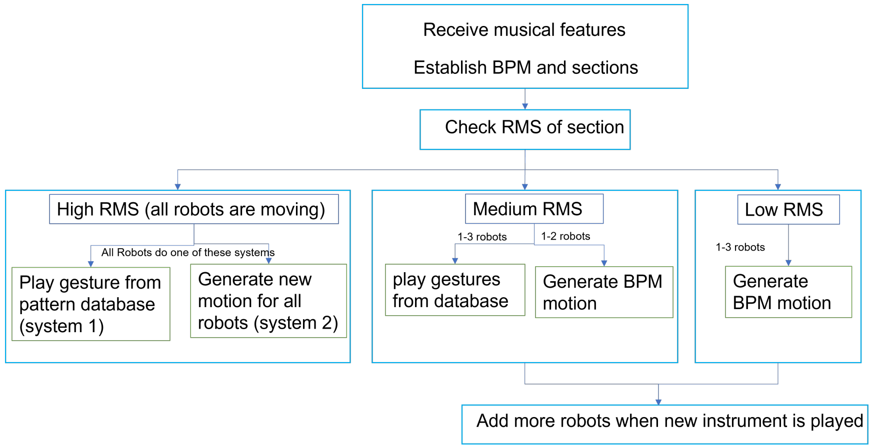

FIGURE 13.11
Dance metrics for full body and body part separation.

As shown in Figure 13.11, the decision tree for the third version made sure that there was always one robot to keep a connection to music playing. The other robots had more complex gestures to keep the choreography engaging.

13.9.2 Discussion

Throughout the design of each system, there was a common trade-off between having intricate gestures and establishing an evident connection from robot movement and music playing. Simple robot movements required a user to make less mental connections in order to see what the robot is doing. However, the simple gestures were not very interesting to the viewer. On the other hand, too many complex gestures tended to be less discreet and more distracting, thereby decreasing the connection between the gestures and the music. Group robot dances were helpful in this aspect because different robots could be doing different gestures. Having at least one robot do simple gestures establishes the connection with the music, while the rest of the robots can do gestures with more engaging and elaborate gestures. According to the analysis, most dances that used the third model had similarly high ratings for HRI and dance metrics, despite working very differently. This could potentially be a result of the impressiveness of a dancing robot arm. Many participants saw dancing robots for the first time in this study, and therefore, may not have picked up on all of the subtle changes. When comparing the second and the third studies, there was increased variety in opinions of the robot. This showed that participants can pick up on subtle differences in dance design.

13.10 Conclusion and Future Work

We presented a comparison between three robotic platforms using EMP and gestures to convey emotions. The studies we presented can suggest broad guidelines and a framework for improving emotion conveyance for non-anthropomorphic robots. Our use of EMP increased the accuracy of identifying a correct gestural emotion and lowered the overall variance. Our results showed that using EMP and gestures gave a recognition rate better than human face detection for three of the four valance-arousal quadrants. Overall, adding EMP was most significant for improving emotion conveyance for the least anthropomorphic robot – The Stretch, followed by the Panda arm, while only causing minor changes for the more social SeekerBot. This reinforces the idea that that robots should have a matching artificial sounding voice to increase their overall perceptions [55]. Each of these gestures was put in a database, for the robots to generate dances based on music

In future work we will continue to improve the emotional gesture portrayal on all platforms through an iterative design experiment methodology, revising and testing our gestures in consecutive user studies. We also plan to implement our gesture design to evaluate specific emotions, and explore the effects of gestures as lube reactions to human input. We also want to further explore new gesture generations methods with a human dancer in hopes of developing a human–robot interactive system. We will use this framework to start developing other types of gestures, and apply these guidelines to implicit gestures. We believe that for future developments in emotion and robotics it is crucial to consider studies with multiple robotic platforms.

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