MASTER

# Expressing emotion through motion

## how speed, smoothness and head position affect a social robot's position on the circumplex model of affect

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# Expressing Emotion Through Motion: How Speed, Smoothness and Head Position Affect a Social Robot's Position on the Circumplex Model of Affect

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## Abstract

Robots are expected to appear in increasingly human environments. To help them communicate with, and be liked and accepted by humans, researchers and designer have been working on giving these robots the ability to express emotions. More often than not, this is done through copying emotion anthropomorphic emotion cues such as facial expressions and gestures. However, this approaches are not enough because they are not compatible with the morphology of some robot, and robots stand to benefit from combining multiple, congruent emotion cues. Since most robots have moveable elements, more abstract motion properties can be manipulated to influence the perceived arousal and valence of the robot, which can in turn influence perceived emotion through the circumplex model of affect.

Forty people participated in a lab study with a 3(speed: slow, medium, fast)x3(smoothness: jerky, medium, smooth)x3(head position: down, forward, up) within-subjects design. A robot moved around the floor and participants rated it on arousal, valence and emotion for all conditions.

There were significant positive relationships of perceived arousal with speed and head position, significant positive relationships of perceived valence with speed, smoothness and head position, as well as an interaction effect of speed and smoothness on perceived arousal, and an interaction effect of head position and smoothness on perceived valence. The relationship of perceived arousal and valence with perceived emotion was also validated in this context.

Manipulating motion properties in social robots appears to be effective in influencing perceived emotion. The results provided evidence for the validity of the circumplex model of affect in the context of emotion expression in HRI, and nuanced some earlier works in the field. These insights can aid robot technologies meet the increasingly social demands of their tasks.

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# Introduction

Designing intuitive interactions between humans and social robots is important because social robots will be increasingly ubiquitous in human environments. Robots have become, and are predicted to continue to be more common in human environments, such as healthcare, education and homes (Robinson, MacDonald & Broadbent, 2014; Sharkey, 2016). They are also performing industry tasks that require more social skills (Heyer, 2010). The potential frustrations of naive humans encountering, but not understanding, these social robots can put a strain on the acceptability of technology. A popular way to remedy this is by cleverly exploiting anthropomorphism. Humans are good at recognizing the emotions of other humans, and will apply these abilities when interacting with inanimate objects such as social robots (Duffy, 2003). This means that when the object acts or looks similar to a human expressing a certain emotion would, humans will attribute that emotion to the object. By tricking humans into attributing human traits such as goals and motives, and personalities and emotions to the robot, robot designers can steer humans to interact with the robot similarly to how they interact with another human, creating more intuitive interactions (Duffy, 2003; Nass, Steuer & Tauber, 1994).

There are different strategies for implementing emotion expression in robots. One approach is copying human or animal facial expressions, gestures, postures and sound. Another way is to forgo nature and synthesize entirely new expressions. This thesis explores how properties of motion can affect a robot's perceived emotion. Rather than looking at specific physical movements associated with an emotion, this approach entails finding the properties of emotion underlying these movements and developing more generalized forms of emotive motion. Motion properties can be manipulated for any robot with visible, moving parts in its morphology, regardless of whether the robot resembles anything human-like.

First I will discuss motivations, related work, and theories of emotion. Then I will describe a lab experiment where participants judged the emotions expressed by a social robot performing different behaviors on emotion. Lastly I will discuss what these results mean and how they should impact the design of social robots.

## Why should robots express emotions?

In human-robot interaction research, the belief has grown that emotions can aid interactions between robots and humans. Generally arguments for the necessity of giving robot the ability to express emotion fall in two categories: Facilitating easier communication and improving evaluations of the robot. Implementing emotion in robots may allow users to interact with them in familiar ways by letting them apply interaction schemas borrowed from human-human interaction (Arkin, Fuijita, Takagi & Hasegawa, 2003; Duffy, 2003). This means that people who have never interacted with a certain robot before may find it easier to communicate with it when the robot expresses and responds to emotions similar to how a human would. Fong, Nourbakhsh and Dautenbahn (2002) argue that the external display of emotion by robots can help communicate their inner state, goals and intentions, and that robot emotions can even act as a control mechanism, where the robot's displayed emotion reflects changes to the environment. In other words, expressing emotions can allow the robot as well as the humans or other robots interacting with it to perform tasks and achieve goals. More generally, non-verbal communication in the form of hand gestures, head gestures and gaze following can aid information presentation and turn management (Meena, Jokinen &

Wilcock, 2012). Brave, Nash and Hutchinson (2005) made a virtual agent that could play blackjack with people. It could empathetically respond to the human player's situation with text and a facial expression, emotionally respond to its own situation, but also respond neutrally. In their experiment participants felt the empathetic agent was more caring, likeable, trustworthy, submissive and supportive. The self-oriented emotional agent was not liked as much, but still more likeable than the emotionless agent. Such traits can be especially important for social robots. For example, healthcare robots can benefit from being perceived as trustworthy and supportive in the field of healthcare, depending on the care tasks (Van Wynsberghe, 2013; Robinson et al., 2014). Furthermore, humans tend to prefer actors with behave similarly as themselves (Nass, Moon, Fogg, Reeves & Dryer, 1995). Copying a person's emotions can be a successful strategy for a robot to make the person like it more. To summarize, capabilities for emotion expression in robots can offer human-robot interactions that are easier, more intuitive and more liked, and they can help both the human and the robot achieve goals.

On the other hand, social robots do not always benefit from being social. Kennedy, Baxter & Belpaeme (2015) found that children learning about prime numbers from a tablet, learned more when studying with a robot teacher that did not behave socially versus one that did. They believe the social aspects caused the role of the robot to change from the children's teacher to their friend. In this context and execution, the social quality of the robot proved to be more distracting from the learning task than helpful. It is therefore good to consider the context and tasks of the robot before deciding whether or not, and how to implement emotion and non-verbal communication in robot (Van Wynsberghe, 2013).

### Emotion expression inspired by the natural world

In human-robot interaction large strides have been made in developing social robots with the abilities to express emotion, using a multitude of approaches. Some work heavily relies on facial expression. The robot Kismet was designed to express emotion using facial expressions, vocal cues and posture. It was also designed to read social cues, have its own emotion regulation system, and learn from interactions (Breazeal, 2000). Paro is a robotic seal used in dementia care. It features expressive moving eyes and body, and noises, that it uses to express its inner emotional states. It can react to touch and sound, and learn new behavior through positive reinforcement (Wada, Shibata, Asada & Musha, 2007). Sophia is a robot that mimics the upper body of a woman. It closely copies human facial expression, and can have a conversation (Sophia, n.d.). Some researchers have attempted to display emotion by recreating expressive body movements such as postures (Beck, Cañamero & Bard, 2010; Beck, Cañamero, Hiolle, Damiano, Cosi, Tesser & Sommavilla, 2013) or walking gait (Van Chien, Sung, Trung & Kim, 2015). All of these approaches share the element of directly copying behaviors as they appear in nature. They are powerful because they cater directly to the ways in which humans (or animals) detect emotions in other humans (Planalp, 1996).

However, many robots do not have humanoid morphologies. In recent years, many robot vacuum cleaners such as the Roomba have been introduced to households, self-driving delivery robots such as the Tug have entered hospital environments, and telepresence robots have found uses in business, education and care. The Roomba's design is well-suited for vacuum cleaning flat surfaces while keeping a low profile, but should it need to communicate emotion then its morphology does not allow for facial expressions, postures or gestures. Goods delivery robots such as the Tug essentially look like a box on wheels because they were designed to navigate around building floors, carrying a convenient amount of goods and allow for easy loading and unloading. Sometimes, it can even be beneficial to not make a robot appear too human, as some features might lead to expectations that the robot is not able or should not be able to fulfill (Duffy, 2003). For instance, giving a robot an advanced human-like face (e.g. Sophia) can lead to humans expecting it to be capable of conversation and thought, even if its purpose only serves to express emotion. When the robot does not deliver on such expectations the robot is at risk of being disappointing, or even creepy. Therefore, it can be beneficial to design the robot such that its appearance (and the abilities that it suggests) matches the tasks it was designed to perform well.

Despite lacking human-like features, some robots still need or would benefit from the ability to express emotion. A cleaning robot could use emotion to express distress when encountering something it is not capable of cleaning, or provide positive or negative feedback to its users. Delivery robots can benefit from emotions to communicate how safe they are to be around, by manipulating their interpersonal distance, where negative emotion expresses larger distances and positive emotions express a smaller distance (Vieira, Tavares, Marsh & Mitchell, 2017). Or they could use emotion to express happiness about delivering a package. A telepresence robot could copy emotions shown by the person on the other end of the call, to regain some of the non-verbal communication lost through teleconferencing. For such applications, copying human morphology does not apply and researchers and designers are forced to try alternative approaches. Even when it is possible to design a robot with emotive facial expressions, postures and vocal cues, it can still be beneficial to implement more emotion expression techniques alongside the aforementioned ones. Using multiple emotion cues can improve emotion recognition if they are congruent (Ruijten, Midden & Ham, 2016; Zaki, 2013; Yilmazyildiz, Henderickx, Vanderborght, Verhelst, Soetens & Lefeber, 2013). One way to expand emotion expression capabilities in robots is to further explore their near-universal ability to move, but in ways that rely less on anthropomorphism and more on abstract properties of motion.

## Expressing emotion through motion

Within engineering, the degrees of freedom problem is a classical problem. When reaching for an object, or moving from place A to place B, the kinematics of a human body allow this to happen in an infinite amount of variations, in terms of motion path and speed profile. For robots this is often the case as well. This creates an interesting challenge: When there is an infinite amount of ways for a robot to perform an action, which option should it choose? Many attempts have been made at satisfactorily answering this question (Flash & Hogan, 1985; Arimoto, Sekimoto & Ozawa, 2005). More recently, research has attempted to uncover whether and how properties of a robot's motion such as speed, acceleration and the size of motion affect a robot's perceived emotion. Several studies studied the underlying properties of motion for people in different emotional states. Researchers have also tried to vary motion properties in robots and measure participants' perceptions of the robot.

### Human motion studies

Pollick, Paterson, Bruderlin and Sanford (2001) made point-light videos of two actors acting out ten different emotions through a knocking and a drinking motion. Participants categorized the point-light captures into ten affect categories. In one version of the experiment the relation between the points were kept as recorded. In another version the image was flipped vertically, and the phase relations between points were scrambled. In the normal version  participants were able to correctly label 30% of the behavior. In the second version, behaviors were correctly identified only 15% of the time. In both cases, participants scored significantly better than chance. The movements were analyzed for duration, average velocity, peak velocity, peak acceleration, peak deceleration and jerk index. Energetic emotions were positively correlated with shorter duration, higher acceleration, higher jerk index, higher average and peak velocity, and lower peak deceleration. The confusion matrices of both versions of the experiment were analyzed using multidimensional scaling, which revealed two dimensions for both. For the regular version of the experiment the dimensions resembled arousal and valence. For the flipped and scrambled version they also found a clear arousal scale, but the meaning of the second scale was unclear. For both analyses, high arousal was linked to higher average velocity, peak velocity, peak acceleration and jerk index, and lower duration and deceleration. The same correlations, but smaller, were found with the negative valence dimension of the first experiment's results (Pollick et al, 2001). The results show that these motion properties were especially good at describing arousal components of emotions. They also show that while information about configuration of body parts is emotion for emotion expression, without it people are still able to make judgments about emotion based on movement speeds.

Sawada, Suda and Ishii studied arm movement of ballet dancers (2003). They instructed ten dancers to express joy, sadness and anger through a short arm movement. The videos were then analyzed to find the maximum speed, maximum acceleration, and total traveled distance for each movement. In a second study participants were able to recognize the intended emotion in the recorded videos. Compared to anger, the movements for joy and sadness showed lower peak arm velocities and accelerations. Sadness was associated with more traveled distance, which the authors interpreted as anger featuring more direct motion.

In another experiment five dancers were filmed performing the same routine while expressing anger, joy, fear and grief (Camurri, Lagerlöf & Volpe, 2003). By making the dancers stick to a routine the researchers prevented the dancers from using more gesture-like expressions, and faces were blurred to hide facial expressions. Without gesture and facial expression cues, participants were still able to categorize of the videos (where the dancers were essentially silhouettes). Analysis of motion differences between emotions showed that anger and joy showed higher quantity of motion and more continued motion, while fear and grief showed more contracted movements, more distinct motion phases, and longer duration.

In these studies of motion the researchers did not focus on finding specific gesture-like movements, but rather on more abstract motion properties that underly expressive motion. A social robot may not have an arm capable of copying the arm movements studied by Sawada et al (2003), but it might very well have an other moveable component in its morphology which can show variations in speed, size or direction of motion.

### Manipulating motion properties in robots

Lee, Park and Nam (2007) tried varying velocity, openness and smoothness in a device called the Emotion Palpus. The Emotion Palpus is a movable antenna, inspired by snails and insects, which can be used to evoke emotion responses. It can be attached to other devices such as monitors, phones and audio devices. In the first experiment, participants judged videos of the emotion palpus. All independent variables were varied over 5 levels. Velocity correlated significantly and strongly with the emotion subscale activation, while smoothness correlated with valence. Openness of motion was predicted to positively affect arousal, but did not have a significant effect on either arousal or valence. In a second experiment, Lee et al. (2007) confirmed their findings using 8 degrees of velocity (along with openness) and 8 degrees of smoothness (along with openness).

In another study participants were allowed to adjust motion properties for waving and pointing motions in a Nao robot for five levels of along the unhappy-happy spectrum (Xu, Broekens, Hindriks, & Neerincx, 2013). Happiness was positively related to hand height, finger rigidness, amplitude, speed, decay-speed, repetition and vertical head position. Hand and head positions represent more gesture-like emotion cues, whereas the others represent properties of motion.

Saerbeck and Bartneck (2010) argued from previous work that relative features have a stronger effect on perceived emotion than absolute features. They did a study examining the effects of manipulating the motion properties acceleration and curvature and measured participants' emotion attributions on the sub-scales valence, arousal and dominance. The authors distinguish between internal and external motion, where internal motion refers to changes in configuration of the body configuration, such as moving limbs, and internal motion refers to motion relative to the robot's surroundings. Two types of robots were used: A Roomba vacuum cleaner robot with a non-human-like appearance was used for external motion. The humanoid robot iCat was used for evaluating internal motion. In the experiment the Roomba moved across the floor. The behavior of the iCat was turning its head to look at two different objects. Acceleration correlated positively with arousal ratings, and high acceleration significantly increased dominance ratings. Curvature had a significant effect on valence, arousal and dominance ratings. The effects on valence and arousal ratings were not directional, but higher curvature (sharper corners) yielded lower dominance ratings. Interestingly, they found no significant differences between the results for the iCat and the Roomba, suggesting that changing motion affected the perception of the two types of robots similarly.

Dang, Hutzler and Hoppenot (2011) used the telepresence robot LINA to move around the room 'in a musical context'. They asked participants to categorize the different behaviors in the affect categories happiness, sadness, anger and serenity. They tried to directly manipulate the valence and arousal dimensions of affect. High speed was used for high arousal, and smooth turning behavior, along with an upward head position was used for high valence. For each of the four motion conditions, the intended emotion was correctly identified by half of the participants or more. Some of the trials were accompanied by a piece of emotive music that the robot was said to be dancing to. Adding music in concordance with the robot's expressive movements improved recognition rates of the robot's emotional state, while music in discordance negatively impacted recognition rates.

Kim and Follmer (2017) manipulated speed and smoothness for five different motion patterns for a ubiquitous robotic interface. Speed had two levels, and smoothness had three: Asynchronous jitter, synchronous jitter, and smooth. The UBI was a swarm of ten small cylinders, roughly one inch wide, with powered wheels that was called UbiSwarm. Videos were made of the different behaviors and rated in a between-subjects online study by 1067 participants on perceived emotion and user experience. Speed was found to positively affect valence ratings. Motion pattern and speed (positively) were found to significantly affect arousal ratings. The rendezvous behavior (collective inward motion) had the highest arousal ratings, and counterclockwise torus behavior (collectively turning in a circle) was rated as displaying the least arousal. Motion pattern was the only significant predictor for dominance ratings, affecting dominance similarly to how it affected arousal. Speed and smoothness positively affected hedonic value, and the behaviors rated highest on hedonic value were dispersion (outward movement) and rendezvous. High speed, both smoothness and asynchronous jitter, and rendezvous behavior yielded significantly higher animacy ratings than low speed, synchronous jitter, and counterclockwise torus behavior. Smoothness was significantly more likeable than jitter. Dispersion behavior and high speed produced higher urgency ratings.

Two related works studied the effects of speed and smoothness of motion on perceived emotion (Zandbergen, 2018; Wetzer, 2018). A (small, humanoid and child-like) Nao robot pointed at objects for the participant to recognize, after which participants guessed the robot's intention, and rated it on valence and arousal. Both found speed to have a positive effect on perceived arousal. Zandbergen (2018) reports that smooth motion was combined with an upward head position, medium smooth motion was combined with a forward head position, and jerky motion was combined with a downward head position. The combination of smoothness and upwards head position positively affected valence ratings. Wetzer (2018) reported that motion smoothness positively affected arousal ratings. Zandbergen (2018) reports that smoothness and head position did not have a significant effect on arousal.

These studies share the conclusion that it is possible to affect perceived emotion in robots by changing properties of motion. However, they do report conflicting results, which can be hard to disentangle because of methodological differences (e.g. which properties were manipulated or measured, and how was perceived emotion measured?).

## Theories of emotion and the circumplex model

Reviews of emotion literature show that it has been studied for as long as people have had an interest in scientifically studying psychology (Calvo & D'Mello, 2010; Moors, 2009). In the 19th century scientists as Darwin and James published their first theoretical musings. Despite pondering the subject for over a century, there are many aspects of emotion that scientists still do not agree on. Generally emotion is a complex concept comprised of multiple components, with a cognitive, feeling, motivational, somatic, and motor component (Moors, 2009). These components serve the purpose of stimulus evaluation, monitoring feelings, preparation for action, and action (Moors, 2009). However, different definitions for these components are common. Furthermore, emotion researchers disagree about how to identify emotion episodes, and what is part of the emotion and what is merely related to it. They also disagree about the order in which the components occur, and how emotions are distinguished from other experiences (Moors, 2009).

One especially relevant topic of debate for the field of HRI is whether to conceptualize different emotions as being constructed from a set of universal basic emotions, or as the emerging experience of a small number of continuous process. The former has often been referred to as the Ekman (1992) view, and has sprung from the observation that for some emotions, facial expressions are consistent among humans (and other species) across cultures and the globe. This has given credence to the idea that different emotions have their own unique pathways hardwired in the central nervous system. Posner, Russell, & Peterson (2005) counter some of the arguments for the basic emotions view. They point out that behaviors of animal species cannot be assumed to reflect corresponding internal states, without brain activity readings to support the claims, or expressions of subjective experience by the animals. They write not to have seen either yet. Nor have they seen brain studies in humans that successfully show separate, hardwired pathways for the subjective experience of basic emotions. They concede that such pathways may exist for the expression and recognition of basic emotions, but the underlying principles may be very different. Instead of ascribing to the basic emotions view, they support the circumplex model of affect (Russell & Mehrabian, 1977; Russell, 1980; Russell, Lewicka & Niit, 1989; Posner et al., 2005). This model proposes that emotions are made up from an arousal component (amount of activation), and a valence component (positive or negative affect). Sometimes dominance is also included. Arousal and valence are theorized to be orthogonal, and emotions can span around this 2D model of affect. This view has been supported by studies into how people's concepts of emotions and ratings of emotion experiences. This theory suggests that distinct emotion categories do not have a physiological basis, but rather they are the result of cognitive appraisals of the physiological experience.

### Reading emotions and cue integration

Designing emotion expression in a robot means that we are creating cues in the environment of the person that is expected to read the emotion. It is important to consider how people read emotions in order to better understand how to present emotion cues. A diary study revealed participants relied on many different cues (Planalp, 1996). They mostly reported using direct vocal, facial, and indirect vocal cues. However, bodily cues, context and the activity of the person being judged were also common cues. Not only are people flexible in which emotion cues are available, they are also flexible with regards to which brains systems they use.

Zaki (2013) argues that while in laboratories researchers have often favored isolated investigations into specific affective cues, in real life – where the task of recognizing affect is often more noisy, complex and rich than in lab settings – people integrate sensory and cognitive emotional cues to make judgments. Different cues are given different weights based on how reliable they are, and Bayesian models have been used successfully to model the integration of perceptual cues. Zaki (2013) argues that the same can be done with social cognition. He gives the example of perceiving a crying athlete as happy, because of a gold medal around the athlete's neck. The perceptual affect cue of crying on its own is unlikely to suggest happiness, but social cognitive aspect of recognizing that the gold medal is something that the athlete is most likely happy with helps us to infer that the athlete is most likely to be ecstatic (Zaki, 2013). Our ability to use multiple cues also becomes apparent when one the capability to read one type of cue disappears. When judging a facial expressing, a person's sensorimotor system is activated to mentally reenact that expression, but also the system responsible for retrieving semantic knowledge about certain aspects of the expression (Davis, Winkielman & Coulson, 2017). When noise is introduced to the sensorimotor system, people are able to adapt by relying more on semantic knowledge (Davis, 2017). Sometimes social cues will not work without the presence of another. Ham and Cuijpers (2015) found that a robot storyteller was more persuasive when the robot gazed at participants, and this effect was stronger when the robot employed body gestures. However, using body gestures while the robot gazed at a point alongside the participants, body gestures did not make the robot more persuasive. The interplay between emotion cues based on motion properties, and emotion cues based on copying expressions, postures and gestures from nature has not been researched exhaustively.

## Predictors of valence and arousal

When gauging the emotion of another person, or social agent, it is not relevant what the underlying basis is for the emotion. What is relevant is that emotional cues are readable. For emotion expressions then, both the theory of basic emotions and the circumplex model of affect can be useful. In the body of research into robot emotion expression introduced above, most of the approaches directly copying expressions and behaviors from nature can be said to ascribe the view of basic emotions. By copying specific behaviors from humans and other animals, they imply a categorical view of emotions, as opposed to a more continuous, two-dimensional view. The work investigating motion properties for emotion expression has mostly borrowed from the circumplex model of affect. All of these papers have addressed this either explicitly, or implicitly by measuring emotion with valence and arousal (and dominance) measures. I will also adopt the circumplex model as the underlying theoretical basis for emotion expression. By giving the impression that the robot is experiencing a certain state of arousal and valence (a position on the circumplex model), a person interacting with this robot will likely ascribe an emotional state to the robot based on those arousal and valence cues. In the following sections the best motion properties for influencing perceived arousal and valence are discussed.

### Predictors of arousal

In most of the motion property studies described above arousal was predicted well by speed. Other predictors were high acceleration and low curvature (Saerbeck & Bartneck, 2010), motion pattern (Kim & Follmer, 2017), and smoothness with upwards head position (Wetzer, 2018). Human motion studies also supported a link between arousal and speed and acceleration, but also high jerk (Pollick et al., 2001). The latter contradicts with Wetzer (2018), as jerkiness and smoothness are opposites. Some studies found the length of behaviors to be shorter for emotions with high arousal (Pollick et al., 2001; Camurri et al., 2003), but that can partly be explained by finished tasks earlier because of higher motion speed. Sawada and colleagues (2003) found that for the high arousal emotions people exhibit more direct motion, but this contradicts with Sawada et al. (2003) who found high arousal emotions to feature larger quantities of motion.

### Predictors of valence

There was less consensus on the best predictor for valence, but most often some form of smoothness was used and supported. Lee (2007), Kim & Follmer (2017) and Zandbergen (2018) and Wetzer (2018) operationalized smoothness variances in speed profile. Saerbeck and Bartneck (2010) and Dang et al. (2011) used smoothness to manipulate perceived emotion by manipulating curvature. However, their results are contradictory. Saerbeck and Bartneck (2010) saw increased valence ratings for both higher and lower curvature, whereas Dang and colleagues concluded that only smoother turns increase valence. Besides smoothness, Kim and Follmer (2017), and Xu et al. (2013) found speed to positively affect valence ratings, but this contradicts with Pollick et al. (2001). Xu et al. (2013) also found repetition to be more common positive emotion.

For the results of Zandbergen (2018) and Dang et al. (2011) it is unclear how much of the effect of smoothness and head position on perceived emotion can be attributed to smoothness.

Neither varied head position and smoothness independently, so it is uncertain how much these factors individually influenced the perceived valence of the robot. It is not unlikely that valence was largely influenced by position of the head, rather than motion smoothness. Head position has been shown to influence how humans interpret emotions displayed by robots (Beck et al., 2010; Beck et al., 2013, Xu et al., 2013). In their studies, pointing the head upwards had the result of people interpreting the robot's behaviors as belonging to emotions associated with higher arousal and valence. Considering that manipulating valence is less easy than manipulating arousal, and also the fact that copying emotion cues from nature has shown to be effective, it is likely that the effect of head position was largely responsible for manipulating valence in Dang et al (2011) and Zandbergen (2018).

### Valence, arousal and emotion

Related works differed in whether they measured perceived arousal and valence or perceived emotion. None did both, assuming that differences in valence and arousal ratings also mean a different perceived emotion, or that an effect on perceived emotion was caused because the manipulation altered the robot's displayed valence and arousal levels. The assumption follows the following logic. The circumplex model of affect states that emotion words can be ordered to form a circle on the plane spanned by two axes that are most often interpreted as valence and arousal. Since this theory is based both on how people experience their emotions, and on how people conceptualize emotions in general, perceived emotions in others should also be related to ratings of the other's arousal and valence. In the context of HRI, when a person associates a certain emotion with a robot's behavior, we should expect that the emotion's position on the circumplex model correlate with the person's actual ratings of the robot's valence and arousal. With this in mind, a researcher could assume that when the robot was rated as more positive and aroused, the robot was more likely interpreted as being happy than sad, an emotion that is characterized as negative and unaroused. Similarly, when a manipulation makes a robot be perceived more often as happy than sad, a researcher might conclude that the manipulation contributed positively to valence and arousal.

Without verifying that valence and arousal ratings actually represent the presumed emotion, or without verifying that differences in emotion recognition rates can be explained through valence and arousal, researchers have to be more careful when drawing conclusions about the underlying theory. Comparing valence and arousal ratings with emotion is non-trivial. Experimentally generated valence and arousal coordinates for emotions do exist (Russell (1977) provides 151 affect words rated by 300 students on arousal, valence and dominance; Hepach, Kliemann, Grüneisen, Heekeren & Dziobek (2011) provide 62 affect words rated by 100 German students on valence and arousal), but no single list is exhaustive. Different lists are based on different methods, and do not necessarily agree with each other.

Moreover, a rating on valence and arousal do not offer the resolution required to assess which exact emotion word, out of hundreds of possibilities, the person thought was most applicable to the robot. Ratings can vary based on whether people judge a concept, a current experience, or an external target (Russell, 1980; Bradley & Lang, 1994). Also, people differ in how they report emotions. For instance, people can be relatively valence-focused or arousal-focused (Feldman, 1995), and differ in how well they can separate different emotions (Feldman Barret, Gross, Conner Christensen & Benvenuto, 2001). Ratings of concepts also depend on lingual and cultural differences (Russell, Lewicka & Niit, 1989).

In short, people experience and report emotions differently, and no perfect mathematical translations between emotion and valence and arousal exists. Therefore, valence and arousal ratings cannot be used to perfectly determine which emotion a person saw in a robot. These findings do not critically challenge the core idea that of the circumplex model that valence and arousal lie at the basis of emotion. Rather, they suggest researchers take care to avoid equating valence and arousal with emotion.

### Research aims

With this thesis I wish to gain further insights in how to manipulate perceived valence and perceived arousal in social robots in order to change their perceived emotion. Previous work has shown to be contradictory in some areas, especially when it comes to predicting valence. Some highly promising results are undermined by methodological problems. In a lab experiment, an attempt was made to replicate effects of motion speed on arousal, and motion smoothness on valence. This leads to following hypotheses. *H1a: Increasing motion speed will positively affect a robot's perceived arousal*, and *H1b: Increasing motion smoothness will positively affect its perceived valence.*

Next, I set out to validate the assumptions made in HRI about the relationship between valence and arousal, and emotion, in the context of robots employing movement for expression. *H2: The coordinates of the theoretical position of a perceived emotion on the circumplex model positively correlate with the actual perceived valence and arousal ratings.*

Lastly, we want to learn more about the interaction between emotive motion properties and emotion cues copied from typical human emotion behaviors. Previous work seems to suggest that human-like emotion cues are better at manipulating perceived emotion across the valence axis. Insights from cue integration suggest that congruently combining emotion cues will lead to better emotion recognition, and that smaller cues are especially useful when primary cues disappear. The study of Ham and Cuijpers (2015) shows that some social cues only work in the presence of others. In the lab study head position was manipulated independently similarly to how it occurred in Dang et a. (2011) and Zandbergen (2018). It is expected to positively affect both perceived valence and perceived arousal. *H3a: Moving the head upward will positively affect perceived arousal. H3b: Moving the head upward will also increase perceived valence.* A possible interaction will be investigated, but no explicit expectations are formulated.

## Method

### Participants

In this study forty participants (22F), with ages varying between 18 and 57 years ($M$ = 23.7, $SD$ = 6.0) rated the emotional value of a robot for different behaviors. Participants were recruited using the J.F. Schouten Database of Participants. This is a database for the largest part comprised of (but not exclusively) students of the Eindhoven University of Technology, where members of the database receive invites for studies through email. Participants were selected on the following criteria: they should be at least 18 years old, not suffer from any visual disabilities, and speak English. They were compensated for their participation with €7.50. They received an extra €2 if they were not affiliated with the university. Several participants were excluded from analysis. This is detailed in the first part of the Results section.

## Design

The study had a 3(speed: slow, medium, fast)x3(smoothness: jerky, medium, smooth)x3(head position: down, forward, up) within-subjects design. The dependent variables were perceived valence, perceived arousal, perceived dominance, and perceived emotion. Participants were exposed to 27 variations of the same task. The order was randomized for each participant.

### Task

In each trial the robot would start moving across in circles counterclockwise. Two points were marked on the floor. While the robot was moving, the participant was requested to press and hold the button corresponding to the point that the robot was closer to at that moment. This task was included to ensure the participant continued observing the robot throughout the entire length of its movement.

### Conditions

The duration of the movement (40 seconds), the radius of the circle (approximately 90 cm) and the acceleration rate of the robot were kept constant throughout the experiment. Speed was manipulated by changing the forward speed of the robot. The levels of speed were 0.08 m/s (slow), 0.16 m/s (medium), and 0.25 m/s (fast). Smoothness was manipulated by introducing short stops of movement at different frequencies. For jerky motion the average time between each break was 3 seconds. For medium smoothness, the average time between each break was 8 seconds. For smooth motion there were no stops. The average length of each stop was set at 0.5 seconds. To make the pattern of stops less predictable, the time between stops, and the length of stops were both varied randomly, 40% around the average. Head position was manipulated by varying the robot's head pitch. Condition 1 and 3 were set to have robot look down (0.5 radian) and up (0.4 radian) respectively, but not too drastically, to ensure that the robot could still be interpreted as gazing at the participant. The middle condition was set 0.05 degrees radian downward such that when the robot moved towards the participant, it gazed directly at the participant's face.

## Materials

The experiment took place in the Virtual Reality Lab (Figure 1) at the Eindhoven University of Technology. This laboratory was well-suited for the floor space demands of this experiment. On one of the far sides of the room a desk and chair were positioned such that the participant had a good view of the robot. At the start of the experiment the robot was positioned approximately two meters away from the desk and three meters away from the chair the participant was sitting on. There were three items on the desk: (1) a laptop with instructions for the experiment and the questionnaires created using LimeSurvey; (2) a

*Figure 1 - Pictures of the experiment set up in the Virtual Reality Lab. The picture on the right shows the view on the robot from the perspective of a participant. As can be seen from the picture on the left, the lab is large enough for the robot to move around.*

wireless keyboard that was connected to a computer in the control room; and (3) a sheet of paper that features a list of twenty-eight different emotions. Two pieces of paper were attached to the floor. One featured the letter 'A' in a large font, and the other featured the letter 'L'. There were two cameras mounted to the ceiling. One was aimed at the robot, and the other was aimed at the participant. The cameras were used for monitoring, no recordings were made. Participants were made aware of this with the informed consent form.

The robot used in this experiment was a Pepper robot, developed by Softbank Robotics. It is a humanoid robot with a moveable head, and a static face. It has moveable arms, a torso and hips, and moves using three omni wheels. On its chest it carries a tablet, which did nothing but play a dark screen saver throughout the experiment. The robot's kinematics offer 20 degrees of freedom. It was programmed with Python 2.7. This robot was chosen for this experiment because it has a moveable head, and can move around the floor without suggesting emotion through a gait.

### Measures

The Self-Assessment Manikin (SAM; Bradley & Lang,1994) scale was used to measure arousal, valence and dominance as perceived in the robot. Each variable is measured with a single 5-point Likert scale, enhanced with a visualization for each response option. One benefit of this scale is that it takes little time to complete, which makes it practical for use in within-subjects experimental designs. Another benefit is that the visualizations help prevent confusion about the direction of the scale and give participants an idea about how the scale is distributed. Dominance is sometimes considered to be an underlying scale of emotion (Russell & Mehrabian, 1977; Saerbeck & Bartneck, 2010; Bradley & Lang, 1994), so while there are no hypotheses in this study about dominance, and dominance will not be analyzed, the measure was still included for possible future work investigating dominance.

The perceived emotion of the robot was measured with an open ended question. The phrasing of the question was as follows: *"What emotion would you most closely associate with the behavior of the robot?"* A reference list of possible emotions was included to help non-native English speakers and to create an idea of what was expected. It contained 28 emotions in random order. The words were ones used by Russell (1980) as they have shown to be distributed across all regions of the circumplex model of affect. 76% of the cleaned up emotion responses were on the reference list.

### Procedure

Participants were first asked to register their participation and sign a consent form detailing the procedure of the experiment and data use and storage. Next, they were asked to sit down at the desk. They were given a brief outline of the experiment and were asked to read more detailed instructions on the laptop. They were instructed to wave at a camera in case of questions. When this occurred, the experimenter would walk into the room to answer the question. After the participant completed reading the instructions, the experimenter reentered the room and asked the participant to explain what they thought they were about to do. If it was clear the participant had misunderstood, they were corrected. The experimenter also asked if there were any words on the list of emotions they did not recognize and clarified if necessary. The experimenter also stressed that the list was merely meant to offer examples, and participants could enter any emotion, provided they felt it was the most appropriate. The experimenter left the room and the participant began a practice trial, before completing the 27 experimental trials. The practice trial featured the medium level for each factor to give participants a reference for the robot's capabilities. In each trial the participant first completed the task described above. After completing the task, they were asked to answer to rate the robot on the SAM-scale and to enter which emotion they most closely associated with the robot's behavior.

# Results

In this section I will firstly report how the robot behaved during the study trials. Next, responses on the SAM-scale are analyzed to test hypothesis 1a, 1b and 3. The last part of this chapter evaluates the relationship between valence and arousal ratings and perceived emotion and tests hypothesis 2.

## Robot Movement

Participants responded to what they perceived, rather than to what code controlled the robot. Therefore, unintentional variations in robot behavior can taint participant responses. This section evaluates whether programmed behavior matches behavior actually performed by the robot. The robot's log file was used to determine whether the robot performed trials as intended. The robot was programmed to vary in speed and smoothness, while keeping the shape and radius of motion constant. The trajectory of the robot is plotted to show how constant the shape and radius of movement really were. Also, speed profiles are analyzed to learn how speed varied between trials. Trials that varied too much from the intended behavior, are considered for removal from the data set used to test the three hypotheses.

### Trajectory

The robot's path was determined from the sensors of the robot's wheels (Appendix B explains how this was done). Figure 2 shows the robot's trajectory, relative to its starting position, for all trials and participants. The width of the line gives an indication of the spread in trajectory within a condition. Color is used to indicate time since the start of the trial (from dark blue (t = 0 seconds) to yellow (t = 40 seconds)). Figure 2 shows that the robot followed a similar circular counterclockwise path for each level of speed and smoothness, with a radius of approximately 0.9 meters. At lower speeds and with less smooth movement the robot traveled less distance. For slow, jerky trials  completed half a circle, while for fast, smooth trials the robot almost two full circles. The image also shows that there was considerable variation within each condition. Figure 3 presents the same data as figure 2, but without the log files for participants 5 and 6. Excluding this data also eliminates most of these large variations. This fits experimental notes that mention the robot was moving at a particularly small radius. The most likely explanation for why the robot behaved differently for these participants is that the robot was overheated. Two trials still look different for the conditions with speed = 2 and smoothness = 1. These belong to participants 12 (speed = 2, smoothness = 1, head position = 2) and 22 (speed = 2, smoothness = 1, head position = 1). Finally, figure 3 shows that as time progresses, differences in robot position within a condition increase. This was expected, as the robot's programming did not employ localization techniques.

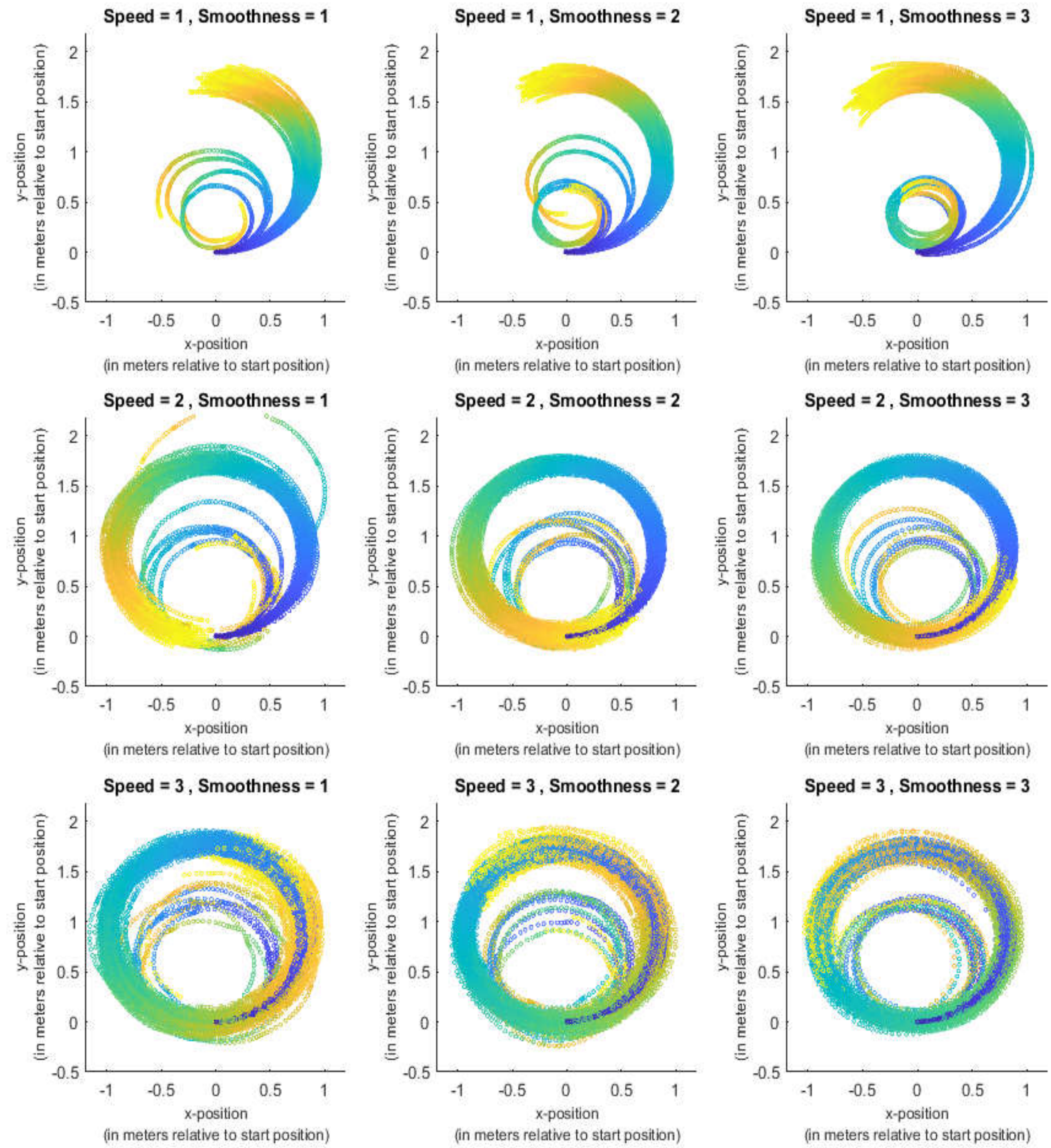


*Figure 2 - Trajectories of the Pepper relative to its position at the start of a trial, for all non-practice trials. Color is used to indicate time, where the start of a trial (t = 0 seconds) is dark blue, and the end of a trial (t = 40 seconds) is yellow. Variations in robot speed and smoothness do not impact the radius of the path. At the lowest speed, the robot was not able to complete one full circle. The image shows variations among trials with the same level of speed and smoothness, with some trials showing a relatively small turn radius.*

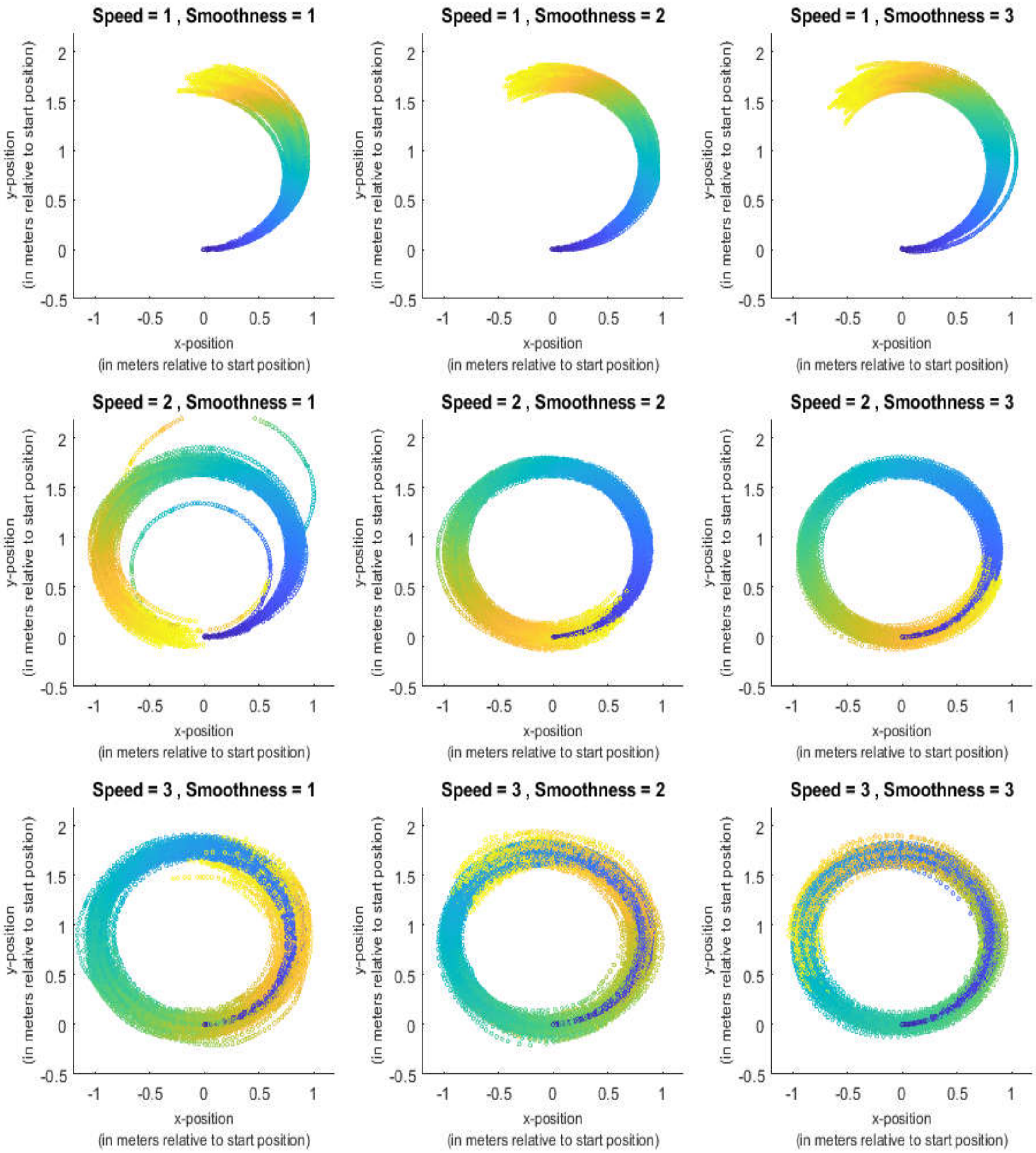


*Figure 3 - Trajectories of the Pepper relative to its position at the start of a trial, for all non-practice trials excluding participant 5 and 6. Color is used to indicate time, where the start of a trial (t = 0 seconds) is dark blue, and the end of a trial (t = 40 seconds) is yellow. Variations in robot speed and smoothness do not impact the radius of the path. At the lowest speed, the robot was not able to complete one full circle. Having these data points removed shows that trials were mostly similar.*

## Speed profiles

Figure 4Figure 4 shows the speed profiles of the robot for all variations of speed and smoothness for a randomly chosen participant (data belongs to the head up trials for participant 40). It shows how variations in time between stops and duration of stops affected the robot's movement for each of the trials. Also, forward velocity remained fairly constant outside of stops, and differences between each level of speed are clear. Slight variations in speed can likely be attributed to the floor of the room not being perfectly flat. It also appears that for higher speeds, the robot was less likely to reach a full stop for a break (most visible for smoothness = 2). However, the sample frequency is not big enough to analyze this in more detail. For several trials, the robot suddenly stopped moving. For smooth trials, the robot did not start moving again until the next trial. For jerky and medium smooth trials the robot continued its trial after the next break. The most likely explanation for this phenomenon is that the robot’s obstacle detection system reacted to a false positive by terminating movement. The robot was programmed in a way to send it as few commands as possible, and it only received new movement commands at the end of each break. Therefore, the robot would not restart movement for smooth trials.

During four of the experiments (participants 1, 20, 25 and 27), an error occurred that caused the wrong trial to be shown to the participant. Rather than seeing each trial once, one would occur twice, and one would not appear at all.

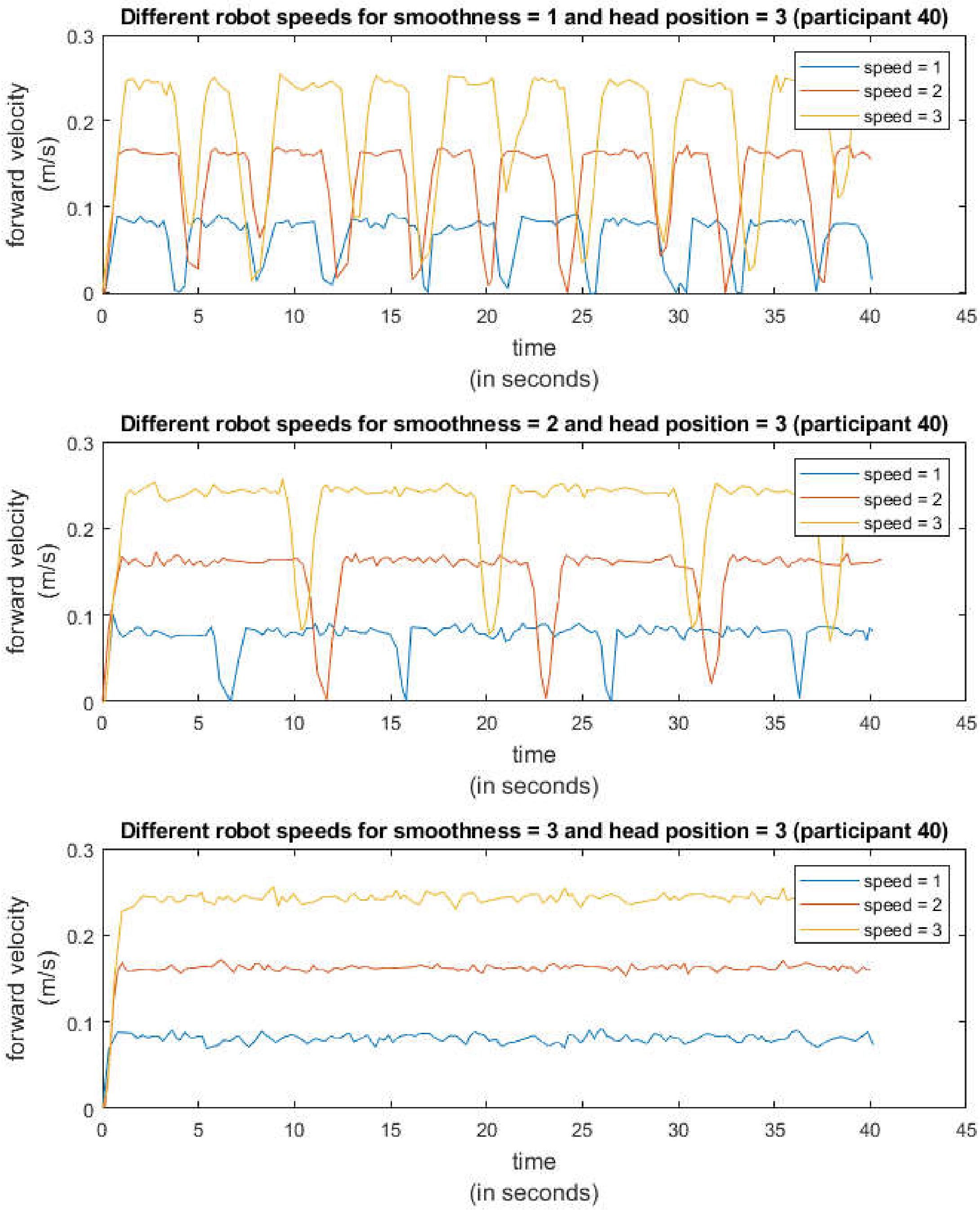


*Figure 4 - Speed profiles for different combinations of speed and smoothness. These were the profiles as produced by the robot in the head-up position for participant 40. Speeds were relatively stable for each trial, but variations did occur.*

## Removing outliers

The four participants (1, 20, 25 and 27) for whom an error in the trial order occurred, had missing data for one condition and double data for another. Therefore, these participants were disregarded in the repeated measures ANOVA analyses, as the analyses required data for each condition. Participants who had a trial where the robot unintentionally stopped moving were not excluded. ANOVA analyses without the latter group of participants did not yield different results. While participant 12 and 22 both saw a trial that differed strongly from the intent, these participants were not excluded because it would be wasteful to throw away 26 good data points because of a single slightly flawed data point. Participants 5 and 6 were excluded from all further analysis, because their trials were too different from the others. This means that ANOVA analyses reported ahead were performed on a sample of 34 participants (20F, $M$ = 22.9, $SD$ = 2.7). The relationship between valence and arousal ratings and perceived emotion was performed on a sample of 38 participants (20F, $M$ = 23.8, $SD$ = 6.1).

### Analysis of Responses to SAM-scale

On average, participants rated the robot 2.96 ($SD$ = 1.13) on valence, 2.71 ($SD$ = 1.08) on arousal, and 2.45 ($SD$ = 1.06) on dominance. Table 1 in Appendix A summarizes arousal, valence and dominance ratings per trial condition.

I will perform two separate tests for analyzing group differences for arousal and valence. Therefore, I will apply a Bonferroni correction and set $\alpha = 0.025$. To analyze group means and effect directions I will perform contrast analyses. Here, I will also apply Bonferroni corrections.

### Analysis of Arousal Ratings

A repeated measures ANOVA was performed on arousal ratings, with the factors speed, smoothness and head position, and their interactions. Histograms and Q-Q plots showed that both the residuals and arousal ratings across all conditions were approximately normally distributed. The Shapiro-Wilk test was rejected in 8 of 27 conditions and the skewness and kurtosis test was rejected in 3 of 27 conditions. Since normality was only rejected in a small number of groups, and visual inspection supports normality, the ANOVA was deemed appropriate. Sphericity was rejected for the factor speed ($X^2(2) = 11.808$, $p = 0.003$), so the Huynh-Feldt correction of degrees of freedom was applied to prevent increasing the chances of type 1 error (Abdi, 2010).

The significant predictors for perceived arousal were speed ($F(1.59, 52.40) = 151.87$, $p <$ 0.001, $\eta_p^2 = .821$), smoothness ($F(1.99, 65.74) = 4.73$, $p = 0.012$, $\eta_p^2 = .125$), head position ($F(2.00, 66.00) = 12.39$, $p < 0.001$, $\eta_p^2 = .273$) and the interaction between speed and smoothness ($F(4.00, 132.00) = 4.20$, $p = 0.003$, $\eta_p^2 = .113$). No significant effects were found for other interaction effects. The total model with only the significant factors was significant ($p < 0.001$, $R^2 = 0.75$, $R^2_{\text{adjusted}} = 0.57$).

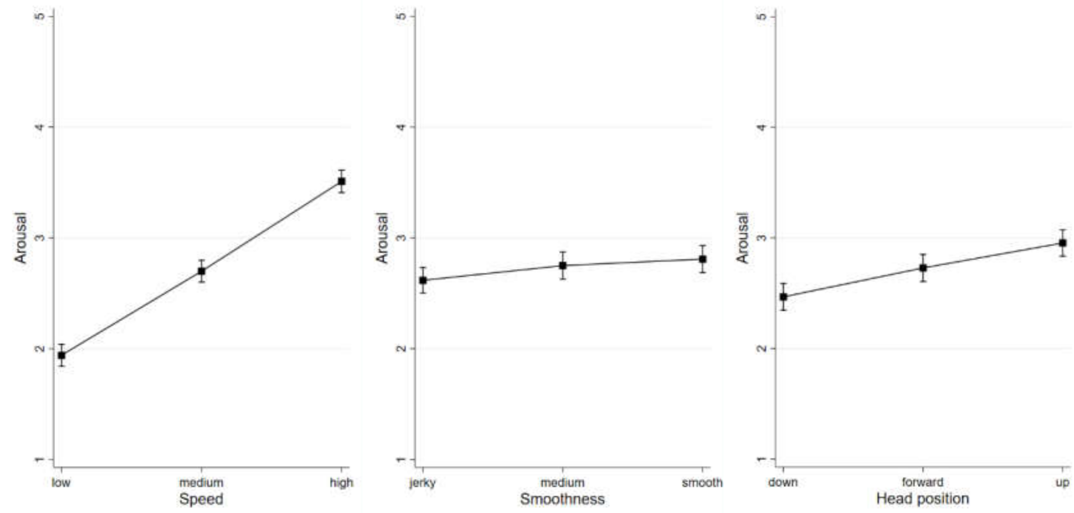


*Figure 5 - Relationship between speed, smoothness and head position levels and arousal ratings of the robot, with 95% confidence intervals. Higher speed, smoothness and more upward head position all correlate with higher arousal ratings.*

Figure 5 shows mean arousal ratings with 95% confidence intervals for different levels of speed, smoothness and head position. The ANOVA test showed a significant effect for all three factors. The figures suggest a strong positive, linear relationship between the robot's speed and its perceived arousal. Upward head position and more smoothness also appear to have a slight positive, linear effect on arousal ratings.

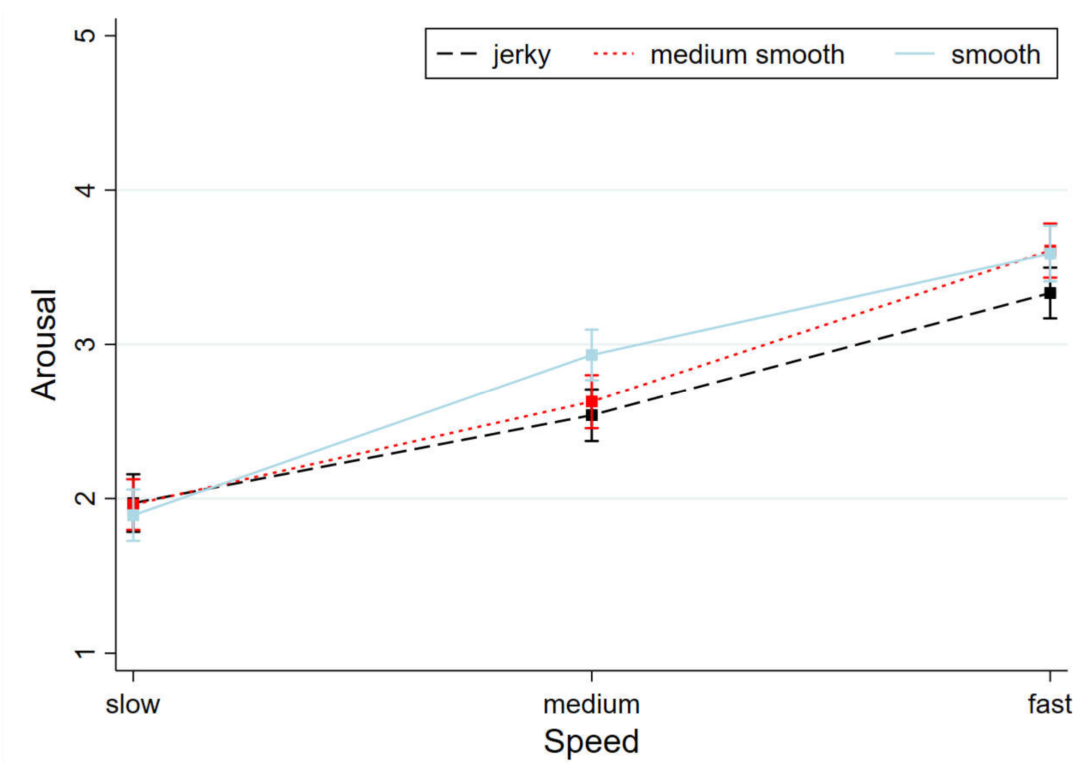


*Figure 6 - Relationship between speed levels and arousal ratings in the robot for each level of smoothness, with 95% confidence intervals. Smoothness appears to affect arousal ratings most strongly for medium speed.*

Figure 6re 6 shows the mean arousal ratings with 95% confidence intervals for different levels of speed for each level of smoothness. It provides insights on the nature of the significant interaction effect between the two factors. It appears the effect of smoothness on perceived arousal is largest for medium speed. So, the interaction effect between speed and smoothness might be a quadratic effect of speed on top of the linear effect of smoothness on arousal.

The contrasts corresponding to the four relationships shown by the graphs were analyzed. Because there are 4 post-hoc tests, a Bonferroni correction should be applied to the α-level to set it from 0.025 to 0.0063. The tests support the linear effects (contrast weights: -1, 0, 1) of speed on arousal ($F(1, 33) = 195.21$, $p < 0.001$, $\eta_p^2 = .855$) and of head position on arousal ($F(1, 33) = 23.58$, $p < 0.001$, $\eta_p^2 = .417$), but not for smoothness on arousal ($F(1, 33) = 7.436$, $p = 0.010$, $\eta_p^2 = .194$). The interaction effect, a quadratic effect (contrast weights: -1, 2, -1) of speed on the linear effect of smoothness on arousal was also supported ($F(1, 33) = 8.54$, $p = 0.006$, $\eta_p^2 = .206$). The significant positive effect of speed on arousal ratings supports hypothesis 1a, and the significant effect of head position on arousal ratings support hypothesis 3a.

## Analysis of Valence Ratings

A repeated measures ANOVA was performed on valence ratings, with the factors speed, smoothness and head position, and their interactions. Histograms and Q-Q plots revealed that both the residuals and valence ratings across conditions were approximately normally distributed. The Shapiro-Wilk test was rejected in 7 of 27 conditions. The skewness and kurtosis test was rejected in 5 of 27 conditions. Considering the small number of normality violations in the groups, and visual inspection suggesting normality, ANOVA was deemed an appropriate test. Sphericity was not violated.

The significant predictors for perceived valence were speed ($F(2, 66) = 56.73$, $p < 0.001$, $\eta_p^2 = .632$), smoothness ($F(2, 66) = 9.85$, $p < 0.001$, $\eta_p^2 = .230$), head position ($F(2, 66) = 358.49$, $p < 0.001$, $\eta_p^2 = .916$) and the interaction of smoothness and head position ($F(4, 132) = 4.75$, $p = 0.001$, $\eta_p^2 = .126$). No significant effects were found for other interaction effects. The total model with only the significant factors was significant ($p < 0.001$, $R^2 = 0.78$, $R^2_{\text{adjusted}} = 0.62$).

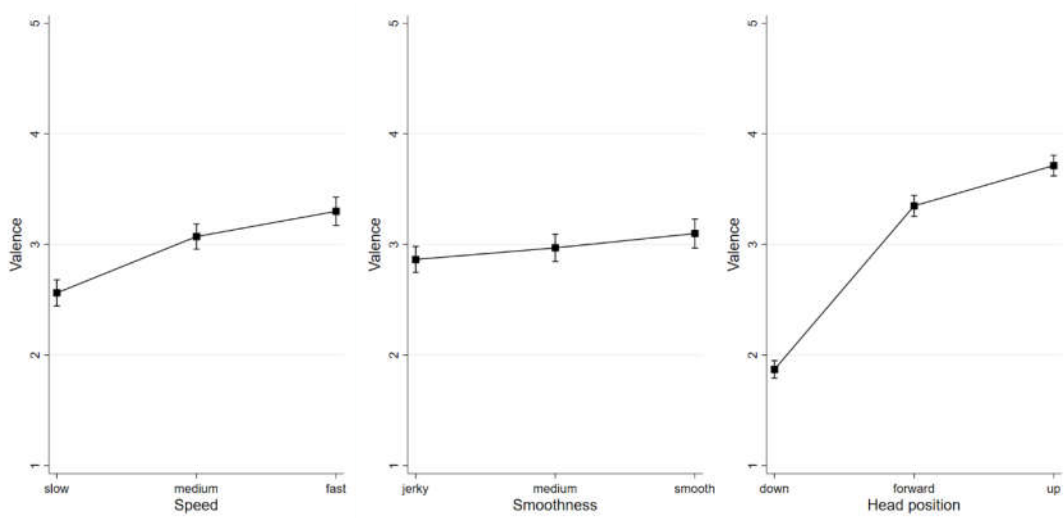


*Figure 7 - Relationship between the robot's speed, smoothness and head position, and valence ratings, with 95% confidence intervals. The graphs show that higher speed, smoother movement and more upward head position produced higher valence ratings.*

Figure 7 shows the mean valence ratings and 95% confidence intervals for each level of speed, smoothness and head position. For all three factors, the graphs show a positive relationship with valence ratings. Figure 8 shows the relationship between head position and valence ratings for each level of smoothness. The effect of smoothness appears to have been strongest when the robot faced forward, less strong when the head faced up, and even disappearing when the head faced down. This suggests that the interaction effect between smoothness and head position is a quadratic effect of head position on the linear effect of smoothness on valence.

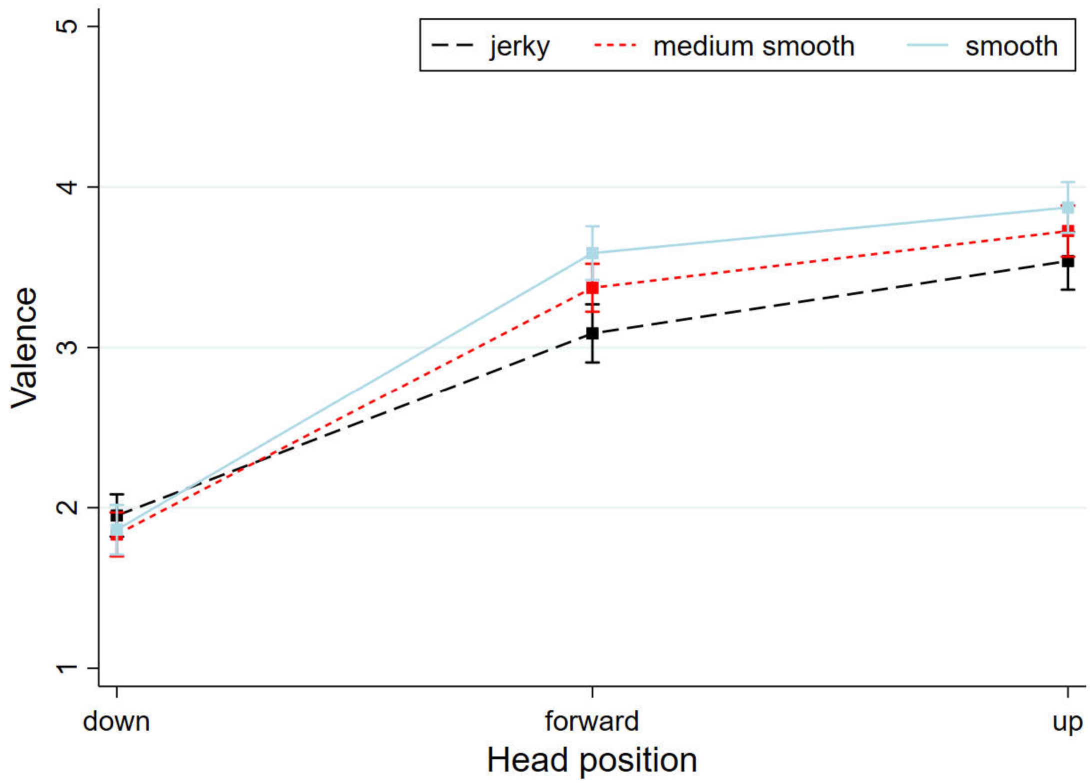


*Figure 8 - Relationship between speed levels and valence ratings of the robot, for each level of speed and smoothness, with 95% confidence intervals. Both speed and smoothness positively affect valence ratings. The effect of smoothness on valence ratings is largest when the head faces forward, and the effect disappears for the downward head position.*

Contrast analyses were performed on the effects suggested above. To correct for doing four post-hoc tests, again a Bonferroni correction is applied and the α-level is set from 0.025 to 0.0063. The contrast analyses support linear effects (contrast weights: -1, 0, 1) on valence of speed ($F(1, 33) = 92.71$, $p < 0.001$, $\eta_p^2 = .737$), smoothness ($F(1, 33) = 17.19$, $p < 0.001$, $\eta_p^2 = .343$) and head position ($F(1, 33) = 465.07$, $p < 0.001$, $\eta_p^2 = .934$). A quadratic effect (contrast weights: -1, 2, -1) of head position on a linear effect of smoothness on valence was also supported ($F(1, 33) = 13.49$, $p < 0.001$, $\eta_p^2 = .290$). The positive effect of smoothness on valence rating supports hypothesis 1b, and the positive effect of upward head position on valence rating supports hypothesis 3b.

### Relationship Between Valence and Arousal Ratings per Group

All three independent variables were all shown to both have a significant effect on both arousal and valence ratings, either directly, through an interaction or both. To more easily understand how each factor alters the robot's position on the circumplex model of affect, figure 9 combines arousal and valence data for each group in the experiment per level of head position.

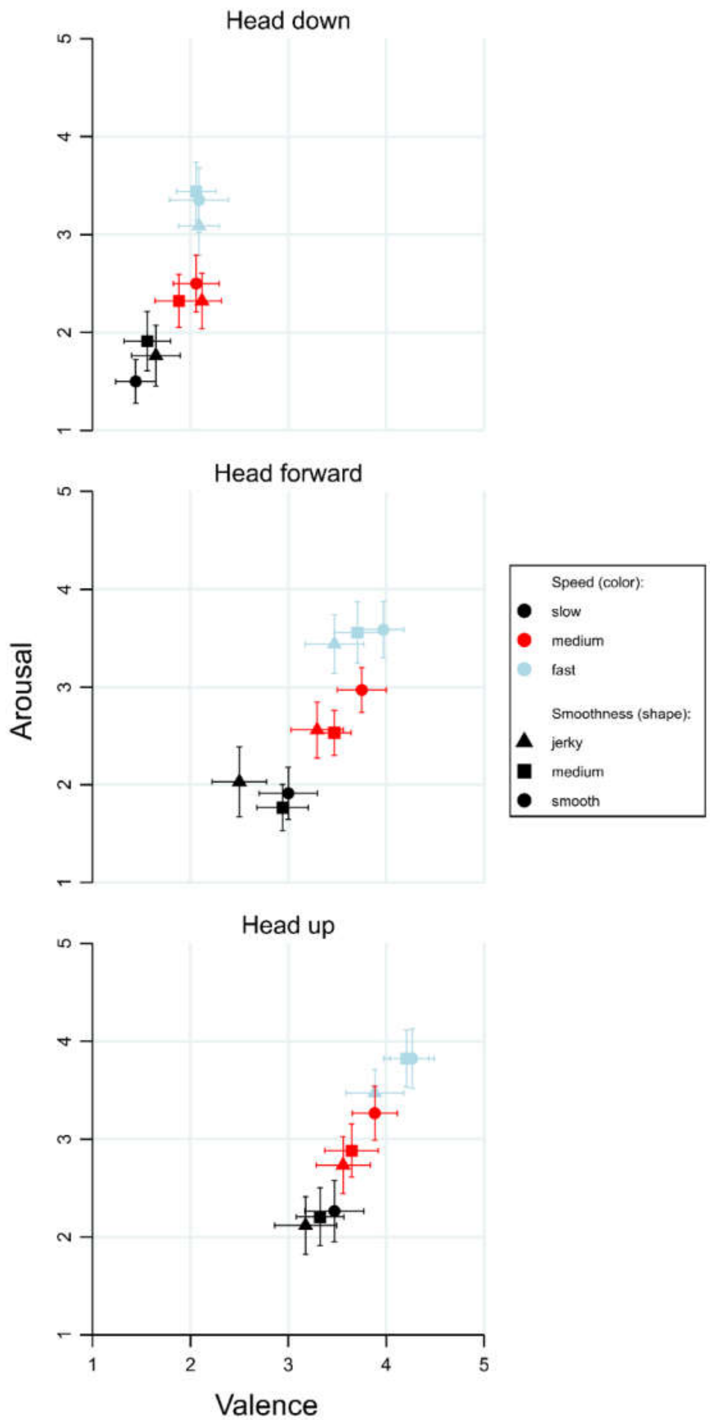


*Figure 9 – These three graphs show how manipulating speed and smoothness affects both valence and arousal for each head position.*

The figure shows that given a head position, speed and smoothness mostly shift the robot's perceived emotion diagonally across the circumplex model, from low arousal and negative valence (depression) towards high arousal and positive valence (elatedness). This suggests a correlation between arousal and valence ratings. Indeed, a significant correlations was found

($r = 0.38$, $p < 0.001$). The motion properties have a greater effect on arousal than valence. Especially for downward and upward head positions, the effect of smoothness and speed on valence is relatively small. However, when the head was aimed forward, the effect of smoothness on valence was much more pronounced.

## Circumplex Model

The valence and arousal ratings do not specify which emotion was perceived. This section explores whether and how perceived emotions corresponded with the ratings.

### Relationship Between Emotion Responses and Ratings of Arousal and Valence

If valence and arousal ratings correlate with perceived emotion, then the distributions of ratings for different emotion categories should have different means. Perceived emotions that fall on the right side of the circumplex model should be expected to be paired with higher valence ratings. When the perceived emotion belongs to the top of the circumplex model, the response should be expected to be paired with a higher arousal rating. To test this relationship all the different emotion responses are categorized into eight areas of the circumplex model (figure 10). Then the correlation of the arousal and valence ratings with the coordinates of these eight areas are tested.

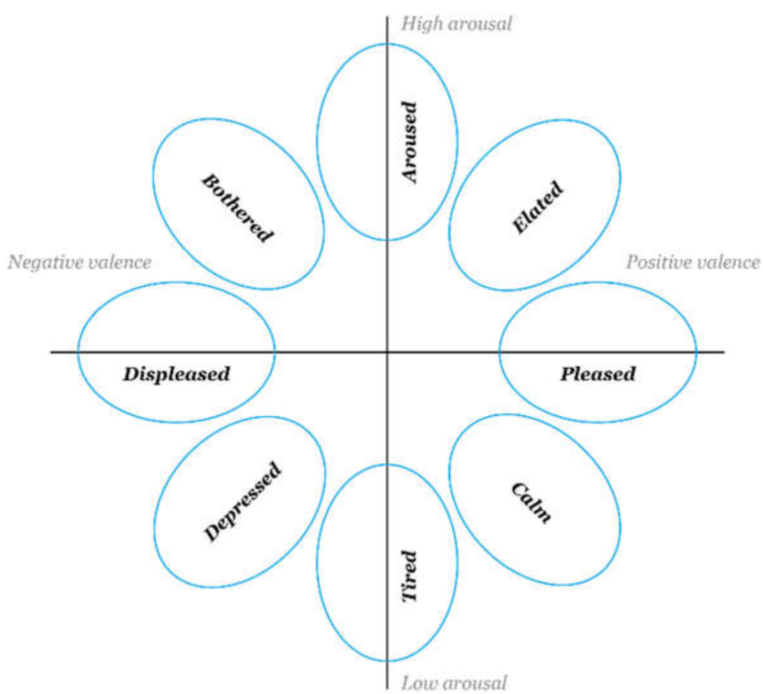


*Figure 10 - Emotion categories around placed on the valence-arousal circumplex model. Emotions associated with the robot's behavior are expected to occur alongside valence and arousal ratings that match the area of the emotion category.*

The most commonly entered emotions were *"happy"* (69 times), *"calm"* (67), and *"sad"* (59). After cleaning up emotion responses, the responses were distributed over the eight general categories that span the circumflex model: Aroused (90°), elated (45°), pleased (0°), calm (315°), tired (270°), depressed (225°), displeased (180°), and bothered (135°). First the words on the emotion example list were categorized based on their position on figure 3 in Russell (1980). Then, the other responses were distributed based on how similar they were to the other words in the category. 28 responses were left out and categorized as 'other'. Reasons included the response was not an emotion, or the participant entering “unsure” indicating the participant not knowing what to enter, or “neutral”. For more details about how emotion responses were cleaned up and categorized, see appendix C.

Figure 11 shows a different heat map for each emotional category (as well as the total responses), and the corresponding frequencies for pairs of valence and arousal ratings. The median rating for each category occurs roughly where it is expected, supporting the relative positioning of emotion categories in figure 10. Only the calm category has its median in the center, rather than the bottom-right. Appendix C includes the same heat maps, but only including the 28 emotion words that were ordered on the circumplex model by Russell (1980).

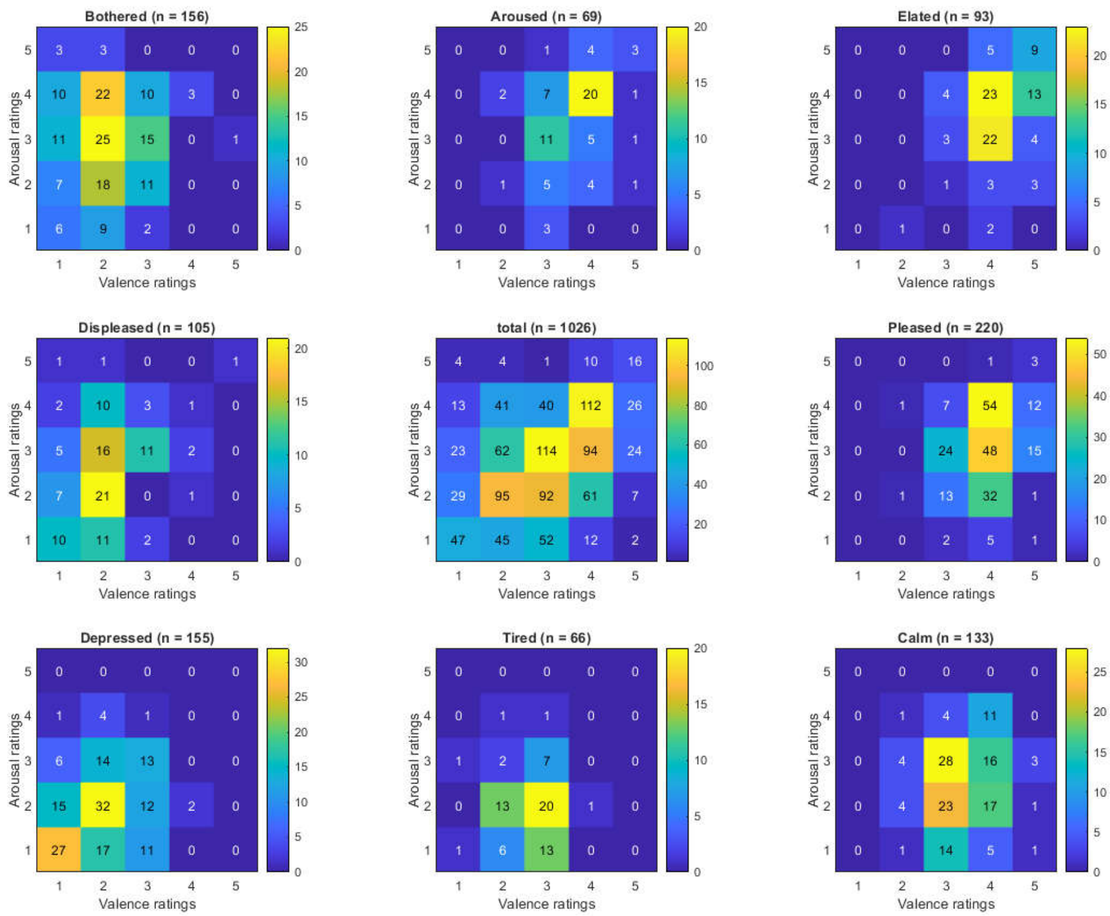


*Figure 11 - Heat maps of valence and arousal ratings for each category of emotion and the total. The numbers reflect the count of how often each pair of valence and arousal ratings occurred for the emotion category. The emotion categories reflect eight different areas on the circumplex model. The ordering of the heat maps is congruent with the position of their conceptual position on the circumplex model. The middle graph is the total count for the experiment. The left three graphs correspond to negative valence, the three maps on the right correspond with positive valence. Arousal is oriented from the bottom to the top.*

To quantify the relationship between emotion responses and valence and arousal ratings, the emotion categories are given a theoretical position on the circumplex model with coordinates (cosα, sinα), where α is the angle that describes the position of each emotion category on the circumplex model. A test is performed on the correlation between these coordinates and the valence and arousal ratings. The ‘other’ category is left out of this analysis. Valence ratings and the valence coordinate of the emotion groups correlate significantly ($r = 0.74$, $p < 0.001$).

Arousal ratings and the arousal coordinate of the emotion groups also correlate significantly ($r = 0.42$, $p < 0.001$). These results, along with how neatly valence and arousal ratings corresponded with emotion responses, as shown in figure 11, support hypothesis 2.

## Discussion

In this thesis I have investigated three things: Firstly, how do motion properties affect a robot's perceived emotion; Secondly, does the relationship of perceived emotion with arousal and valence, work as predicted by the circumplex model of affect in this context; Finally, how do motion properties affect perceived emotion when used alongside other affect cues? A lab experiment was conducted to answer these questions, where participants reported the perceived state of a moving robot as motion speed, motion smoothness and head position were manipulated.

Perceived arousal was positively affected by motion speed, and perceived valence was positively affected by motion smoothness. This is congruent with hypothesis 1 and findings of Lee et al. (2007), Dang et al. (2011) and Zandbergen (2018). However, motion speed was also found to have a positive effect on perceived valence, and motion smoothness positively affected perceived arousal for medium speeds. While the hypothesis is supported, the different manipulations of motion properties were limited in how they managed to influence ratings across the valence-arousal plane. Firstly, the effects of speed and smoothness were not orthogonal, as both speed and smoothness influenced both valence and arousal ratings positively. Therefore, speed and smoothness can be used to make a robot appear more elated or depressed, but not as easily to make the robot appear more bothered or calm. Secondly, the effects of smoothness on arousal and valence ratings were both smaller than the effects of speed. Nevertheless, experiment results support once again that motion properties are can influence a robot's perceived valence and arousal.

Since there was a demonstratable link between perceived arousal and valence, and perceived emotion – supporting hypothesis 2 – we can conclude motion properties were able to influence perceived emotion as well. This link is often assumed without validation in this area of research. With this empirical evidence, the effect of motion properties on perceived arousal and valence can more reliably be assumed to also reflect changes in perceived emotion of a robot. Moreover, the link builds upon the body of evidence in support of the circumplex model of affect (Posner et al., 2005) by showing that not only do humans use arousal and valence to gauge their own emotional states, but they can also use this mechanism to gauge the emotional state of external agents.

Head pitch was shown to positively correlate with both arousal and valence, congruent with earlier findings (Beck et al., 2010; Beck et al., 2013; Xu et al., 2013) and supporting the third hypothesis. Reflecting on Dang et al. (2011), and Zandbergen (2018), it seems more likely that in their experiments head position more strongly influenced emotion judgments and valence and arousal respectively, than smoothness of motion. This is even more evident considering the effect of smoothness on valence was strongly diminished when the head pointed up or down, rather than forward, because Dang et al. (2011) and Zandbergen (2018) did not include a condition where the head gazed forward.

The reason why the effect of smoothness on valence was smaller for upward or downward head positions could be explained with cue integration theory. People attach more importance of stronger and more reliable cues (Zaki, 2013), but when that cue disappears we can rely on weaker cues again (Davis, 2017). Head position can be a strong, unambiguous cue with gazing down suggesting sadness, and gazing up suggesting happiness while gazing forward is more ambiguous (Beck et al., 2010), and when head position does not tell people about the emotion of the robot, then they will more likely pay attention to a weaker cue such as smoothness. Likely, the same applies for the effect of smoothness on arousal and speed, where the effect of smoothness on arousal diminishes for high and low speed.

For robots that are not capable of anthropomorphic emotion expression, manipulating motion properties For robots capable of strong anthropomorphic emotional cues, considering motion properties with smaller effect sizes, such as smoothness, can still be beneficial. This is because motion properties are always present, whether they were designed or not. Accidentally designing incongruent emotional cues may lead to problems such as worse recognition (Ruijten et al., 2016).

### Limitations

Giving social robots the ability to express emotion has previously been found to help increase ratings of likeability, trustworthiness and liveliness (Brave et al., 2005). Such findings have motivated further studies into robot emotions, including this thesis. However, the experiment did not include any measure of likeability. Therefore it is unknown whether participants actually liked how emotion was expressed. The reason for this was that any added measure would have to be included 28 times, thus drastically elongating the duration of the experiment. A few participants commented that they felt the robot seemed quite stiff, another commented that he felt the robot could have benefited from using more different postures.

In the experiment, participants judged the robot's behavior from behind a desk. This context does not resemble any real-world scenario, but is similar to situations where a person sees a robot performing a task at a close distance, such as vacuuming, delivering products, or scanning a reception hall or store for people to engage contact with. However, it is not as representative for contexts where the person is directly interacting with a robot, such as: giving instructions to the cleaning robot, accepting a delivery from a robot, or receiving a welcome talk from a robot. The Pepper robot that was used for the experiment has a human-like face, torso and arms. While, it is possible that results could have differed for robots that are less human-like, previous research has shown that altering motion properties affects valence and arousal ratings similarly for humanoid and non-humanoid robots (Saerbeck & Bartneck, 2010).

The use of ANOVAs to compare means on Likert scale responses between groups has been criticized (Kuzon, Urbanchek & McCabe, 1996). Likert scales are by definition ordinal, and not interval scales. Therefore the distance between responses cannot be assumed to be equal. Moreover, unlike normal distributions, Likert scales do not have infinite tails. This would violate assumptions of normality. However, the central limit theorem states that even when a population is not normally distributed, the sample means of that likely distribution will be, when the sample is large enough. Furthermore, while Likert scales have been shown to affect distributions of the target variable, parametric tests have also been shown to be resilient to this (Harpe, 2015). Harpe recommends that single item Likert scales can be analyzed with parametric tests given that 1) the scale has at least 5 points (that are actually used by participants), 2) the test makes sense given the research question, and 3) normality has been sufficiently considered. Norman (2010) goes even further and argues that because extreme violations of normality barely affect ANOVA test outcomes, it does not make sense to worry about how Likert scales skew distributions, because the distribution does not matter much. These arguments show that while it would have been preferential to measure perceived arousal and valence in a less subjective way, the mere fact that Likert scales were used in this type of analysis should not invalidate these findings at all.

## Future work

In this study only two motion properties were manipulated in order to influence arousal and valence. Speed and smoothness were included because they are the most commonly reported influencers of emotion. Besides speed and motion smoothness, it is possible to include more motion properties for the purpose of emotion expression. Camurri et al. (2003) found length of motion, as well as length and frequency of pauses between movements to vary between different emotions. Relatively short movements were found to be linked with anger. Furthermore, happiness was linked to variable movements, while in this study each property was kept constant throughout a trial. Other motion properties include acceleration profile, how directly goals are approached, openness of motion, and how a robot responds to user probes (Weerdesteijn, Desmet & Gielen, 2005). The present study was another proof of concept for manipulating emotion using properties of motion, but learning more about how other properties affect perceived emotion can only improve the idea. For example, there is still a need to find motion properties that can influence perceived emotion in the angry-calm direction and length of motion could be a useful cue in that regard.

## Conclusion

Ultimately the challenge of social robots lies in designing technologies that are appropriately capable at and acceptable for performing useful tasks. When any of those conditions are not fulfilled a robot will not be able to be of much use. This thesis aimed to further knowledge about emotion expression though the manipulation of motion properties. The gathered knowledge can be used to implement emotion expression for non-humanoid robots that lack the ability to copy human emotion cues such as gestures and facial expressions. Designers of humanoid robots can use these findings to be mindful of how certain motion properties affect the effectiveness of humanoid emotion cues, but also to enrichen the robot's emotion cues vocabulary. After all, humans use many different cues for expression and interpretation of emotions. By adding to the body of work investigating robot emotion I hope to improve the acceptability and capability of robots operating in social environments, where emotions can serve to aid communication between humans and robots and create richer interactions.

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## Appendix A - Calculating Robot Speed and Position

Table 1

*Tabulation of valence, arousal and dominance ratings for each trial condition.*

| Trial Condition | | | | Valence | | Arousal | | Dominance | |
|---|---|---|---|---|---|---|---|---|---|
| *Head position* | *Speed* | *Smoothness* | *n* | *M* | *(SD)* | *M* | *(SD)* | *M* | *(SD)* |
| Down | | | | | | | | | |
| | Slow | | | | | | | | |
| | | Jerky | 38 | 1.68 | (0.74) | 1.74 | (0.89) | 1.76 | (0.91) |
| | | Medium | 38 | 1.58 | (0.72) | 1.89 | (0.89) | 1.89 | (1.06) |
| | | Smooth | 37 | 1.46 | (0.61) | 1.51 | (0.65) | 1.54 | (0.77) |
| | Medium | | | | | | | | |
| | | Jerky | 39 | 2.13 | (0.57) | 2.33 | (0.81) | 2.21 | (0.92) |
| | | Medium | 39 | 2.00 | (0.83) | 2.36 | (0.81) | 2.03 | (0.93) |
| | | Smooth | 37 | 2.05 | (0.70) | 2.46 | (0.84) | 2.22 | (1.08) |
| | Fast | | | | | | | | |
| | | Jerky | 38 | 2.11 | (0.61) | 3.11 | (0.89) | 2.53 | (1.01) |
| | | Medium | 38 | 2.08 | (0.63) | 3.45 | (0.86) | 2.87 | (0.99) |
| | | Smooth | 38 | 2.08 | (0.88) | 3.34 | (0.94) | 3.00 | (1.25) |
| Forward | | | | | | | | | |
| | Slow | | | | | | | | |
| | | Jerky | 39 | 2.51 | (0.79) | 1.95 | (1.02) | 1.85 | (0.81) |
| | | Medium | 37 | 2.89 | (0.84) | 1.84 | (0.73) | 1.89 | (1.02) |
| | | Smooth | 38 | 2.97 | (0.85) | 1.95 | (0.77) | 2.18 | (0.93) |
| | Medium | | | | | | | | |
| | | Jerky | 38 | 3.24 | (0.79) | 2.53 | (0.86) | 2.18 | (0.77) |
| | | Medium | 38 | 3.42 | (0.64) | 2.68 | (0.93) | 2.45 | (0.94) |
| | | Smooth | 38 | 3.68 | (0.77) | 3.03 | (0.68) | 2.49 | (0.84) |
| | Fast | | | | | | | | |
| | | Jerky | 38 | 3.42 | (0.86) | 3.39 | (0.89) | 2.84 | (0.86) |
| | | Medium | 38 | 3.68 | (0.77) | 3.58 | (0.92) | 3.05 | (1.04) |
| | | Smooth | 38 | 3.92 | (0.67) | 3.63 | (0.82) | 3.24 | (0.97) |
| Up | | | | | | | | | |
| | Slow | | | | | | | | |
| | | Jerky | 38 | 3.13 | (0.93) | 2.16 | (0.89) | 2.39 | (0.95) |
| | | Medium | 38 | 3.26 | (0.83) | 2.18 | (0.93) | 2.18 | (1.06) |
| | | Smooth | 38 | 3.37 | (0.91) | 2.24 | (0.88) | 2.37 | (1.17) |
| | Medium | | | | | | | | |
| | | Jerky | 37 | 3.54 | (0.80) | 2.78 | (0.85) | 2.49 | (0.90) |
| | | Medium | 39 | 3.62 | (0.78) | 2.85 | (0.78) | 2.49 | (0.94) |
| | | Smooth | 38 | 3.84 | (0.68) | 3.18 | (0.87) | 2.68 | (0.87) |
| | Fast | | | | | | | | |
| | | Jerky | 38 | 3.84 | (0.86) | 3.39 | (0.72) | 2.89 | (0.95) |
| | | Medium | 38 | 4.18 | (0.65) | 3.79 | (0.84) | 3.16 | (0.95) |
| | | Smooth | 38 | 4.24 | (0.68) | 3.79 | (0.99) | 3.24 | (1.10) |
| | T*otal* | | | | | | | | |
| | | | 1026 | 2.96 | (1.13) | 2.71 | 1.08 | 2.45 | 1.06 |

## Appendix B – Determining the Robot's Path from Wheel Sensor Values

During the experiment trials the robot saved sensor values for its three omni wheels into a log file. These values were used to calculate an approximation of the robot's path during a trial. For each time stamp the sensor values were calculated into a forward and sideways component in m/s, relative to the center of the wheels, as well as the rotational speed of the robot in rad/s. These were then aggregated per trial to find the robot's path, and plotted in figure 2-4.

Figure 12 12 shows the arrangement of the robot's wheels. The center of the robot's rotation was assumed to be the center point of the wheels. From this point, the distance to the center of each wheel was 176.20 mm. The angle ($\varphi$) between the back wheel and each of the front wheels was 118.4°. The wheels are oriented at a right angle from the center point, such that a positive rotational speed of a wheel contributes to a negative rotational speed of the robot. The angle α was equal to φ – 90°, or 28.4°. Because the wheels are omni wheels, they allow free lateral movement as well. They aid to relieve friction that would occur with regular wheels moving in different directions. Movement in the lateral direction of the wheels was not measured.

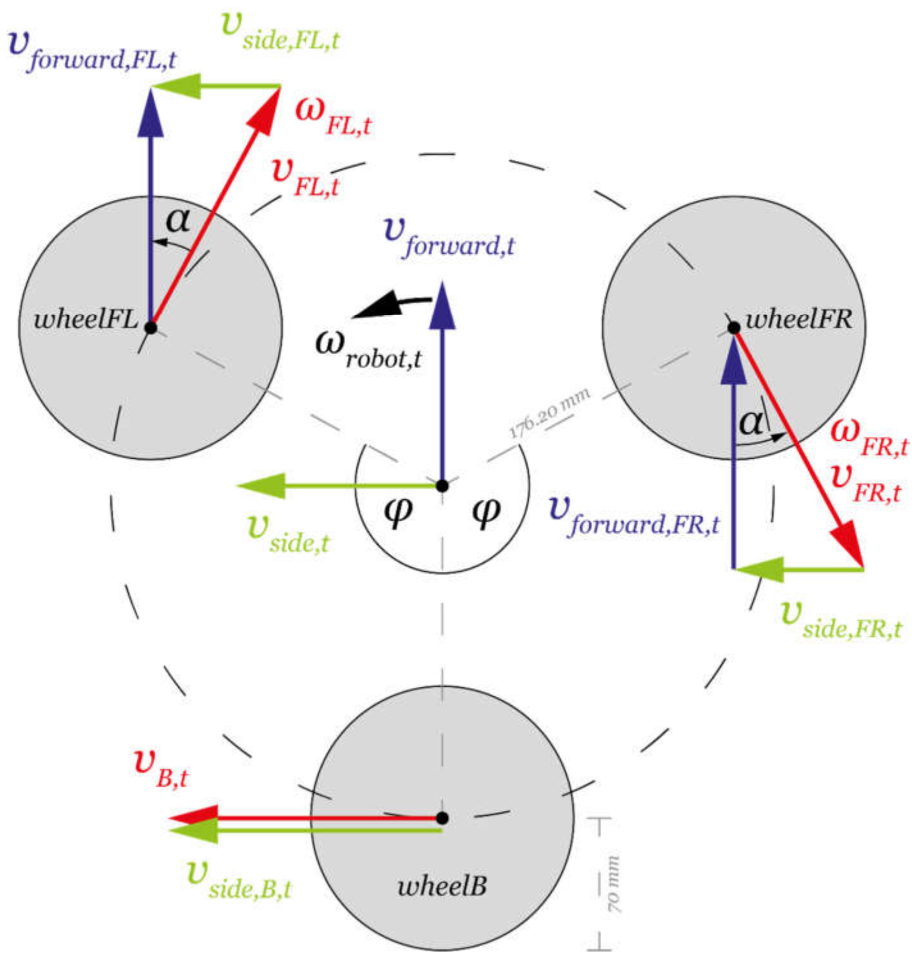


*Figure 12 - Arrangement of the wheels of Pepper robot, as viewed from above.*

### *Finding the robot's position*

The robot's path was calculated relative to the robot's starting point of the trial, with the robot facing along the x-axis.

$$(x_0, y_0, \theta_0) = (0\,m, 0\,m, 0\,rad)$$

Each subsequent point on the path was calculated using the robot's current forward speed ($v_{forward,t}$ in m/s), sideward speed ($v_{side,t}$ in m/s) and rotational speed ($\omega_{robot,t}$ in rad/s), its position ($(x_{t-1}, y_{t-1})$) and rotation ($\theta_{t-1}$) for the previous time stamp, and the difference in time between the current and previous time stamp ($\Delta t$ in seconds).

$$x_t = x_{t-1} + (v_{forward,t} * \cos\theta_{t-1} - v_{side,t} * \sin\theta_{t-1}) * \Delta t$$

$$y_t = y_{t-1} + (v_{side,t} * \cos\theta_{t-1} + v_{forward,t} * \sin\theta_{t-1}) * \Delta t$$

$$\theta_t = \theta_{t-1} + \omega_{robot,t} * \Delta t$$

### *Finding the robot's current forward, sideward and rotational speed*

The robot's forward speed was determined using the forward speed components of the individual wheels. Since the speed of the robot's back wheel was measured orthogonally from the forward direction, there was no forward speed component for this wheel and thus it was omitted. The forward speed of the robot was calculated as the average of the forward speed components, as the front-left and front-right wheels are equally far apart from the center point.|

$$v_{forward,t} = \frac{v_{FL,forward,t} + v_{FR,forward,t}}{2}$$

In the sideways direction, the wheels were not equally far away from the center point. The back wheel was 176.20 mm away ($l_1$), while the two front wheels were 83.8 mm away $l_2$. Assuming that a difference between sideward speed components of the front wheels and the back wheel occurred because the robot was turning, the sideward speed was calculated as follows.

$$v_{side,t} = v_{B,side,t} + l_1 \frac{\left(\frac{v_{FL,side,t} + v_{FR,side,t}}{2} - v_{B,side,t}\right)}{l_1 + l_2}$$

The rotational speed of the robot of the robot was determined using the rotational speeds of the wheels, as well as distance between the center point and wheels, and the radius of the wheels. The wheels' sensors measure orthogonally to the distance from the center point, but a positive wheel rotation contributed to a negative rotation for the robot.

$$\omega_{robot,t} = \frac{-r_{wheel} * (\omega_{FL,t} + \omega_{FR,t} + \omega_{B,t})}{3l_1}$$

### *Finding the individual wheels' forward and sideward component*

The wheels' rotational speeds in rad/s were converted to a speed in m/s and subsequently separated into a forward and sideward component.

$$v_{FL,t} = r_{wheel} * \omega_{FL,t}$$

$$v_{FR,t} = r_{wheel} * \omega_{FR,t}$$

$$v_{B,t} = r_{wheel} * \omega_{B,t}$$

$$v_{FL,forward,t} = v_{FL,t} * \cos\alpha$$

$$v_{FL,side,t} = -v_{FL,t} * \sin\alpha$$

$$v_{FR,forward,t} = -v_{FR,t} * \cos\alpha$$

$$v_{FR,side,t} = -v_{FR,t} * \sin\alpha$$

$$v_{B,side,t} = v_{B,t}$$

## Appendix C – Processing Emotion Responses

This section describes how emotion responses were processed. First, different variations of the same word (*"worried"* and *"worrying"*) were all changed to one variation. This includes misspellings. Secondly, when participants entered multiple words, they were condensed into one. When the words were similar, the first word was kept. When the words had a very different meaning, the words were replaced with a word that best summarized both, if possible.

Next the words were categorized into eight categories. These categories were chosen such that theoretically they spanned a circle around the center of the circumplex model, with each category 45 degrees from the next. The categories were: Aroused, elated, pleased, calm, depressed, displeased, and bothered. First, the 28 emotions that were categorized in a study by Russell (1980) were placed in one of the eight emotion categories according to their position on the circumplex model in figure 3 of that paper. These were the words that were provided as example emotions. Other entries were then judged on how similar they were to the 28 already categorized words. Eighteen words did not fit into either and were placed into an 'other' category. Examples include "bit simple", "bland", "unsure", "drunk" and "high".

The categorization were used to test the relationship between valence and arousal ratings, and emotion responses. However, categorizing emotion responses is a tricky and non-precise process. It is not a completely objective process to judge whether an emotion is more similar to one than the other emotion. Figure 13 shows the same heat maps as presented in the results section, but with only the emotion responses that were ordered in table 3 in Russell (1980). This set of graphs is relatively free from arbitrary decisions and hand-waiving, but it looks almost identical. This leads me to believe that the categorization process was not unfair.

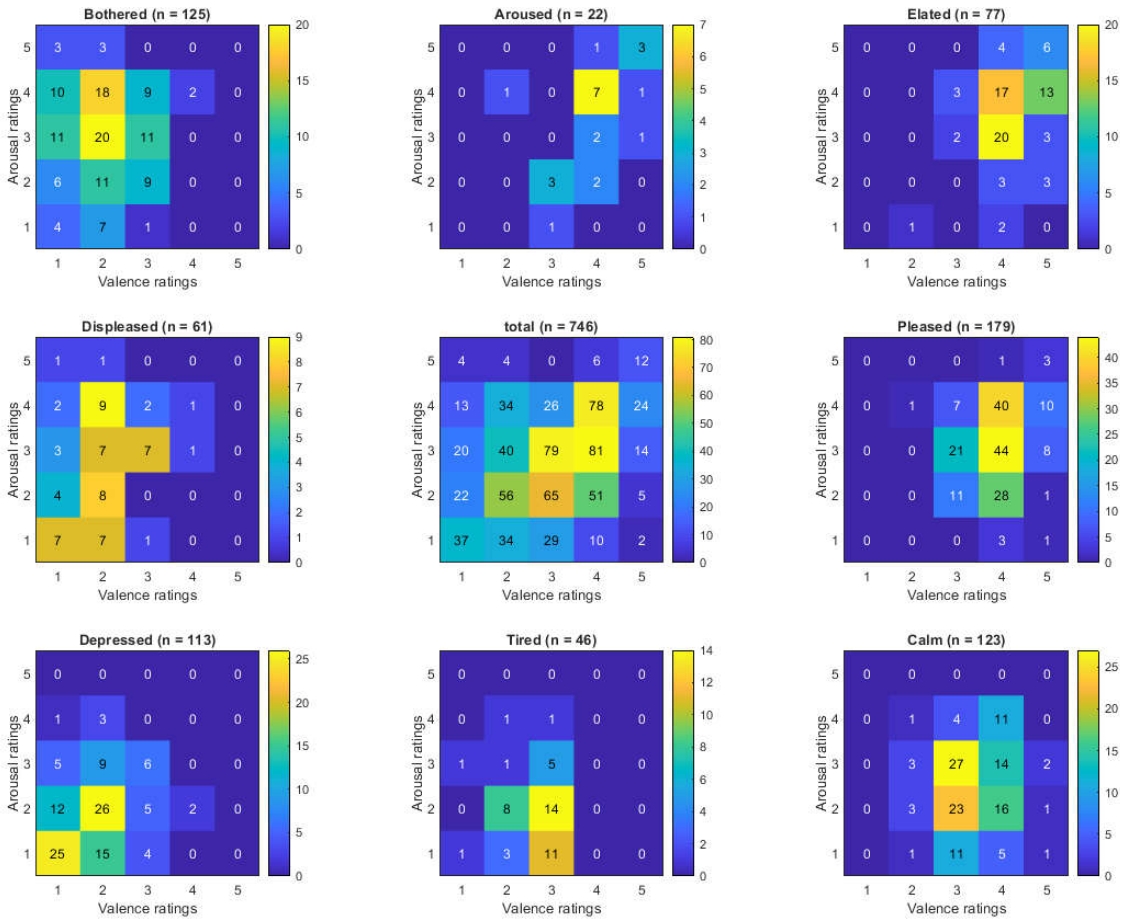


*Figure 13 - Heat maps of valence and arousal ratings, for every emotion category. These graphs only include trials where participants entered an emotion that was on the example list.*

Table 2

*Overview of every unique emotion response and how it was processed. When the 'changed into' cell is empty, that means the response was not altered.*

| *Original word* | *Changed into* | *Emotion category* |
|---|---|---|
| a little excited | Excited | elated |
| accomplished | | pleased |
| active | | aroused |
| active but cautious | anxious | bothered |
| afraid | | bothered |
| alarmed | | bothered |
| alarmed and active | Alarmed | bothered |
| alert | | aroused |
| amazed | | elated |
| angry | | bothered |
| angry, agitated, insecure, little sad | Angry | bothered |
| angry, busy, bothered | Angry | bothered |
| angry, stressed, agitated, insecure | Angry | bothered |
| angry/frustrated | angry | bothered |
| annoyed | | displeased |
| anry | Angry | bothered |
| anxiety | Anxious | bothered |
| anxious | | bothered |
| apologetic | | bothered |
| aroused | | aroused |
| aroused, mischievous | Aroused | aroused |
| ashamed | | displeased |
| astonished | | aroused |
| at ease | | calm |
| attentive | | elated |
| awake but not very energetic | Drowsy | tired |
| Awake | | aroused |
| awkward | | displeased |
| balanced | | pleased |
| bit afraid | afraid | bothered |
| bit simple | Simple | other |
| Bland | | other |
| Boosted | | elated |
| Bored | | depressed |
| Bossy | | aroused |
| Bothered | | bothered |
| bothered by everything. angry-ish | Bothered | bothered |
| busy | | aroused |
| busy, in a hurry, but positive | Busy | aroused |
| calm | | calm |
| calm, positive, happy, ready to help, little too confident | Helpful | pleased |

| *Original word* | *Changed into* | *Emotion category* |
|---|---|---|
| calm, relaxed | Calm | calm |
| care-free | | pleased |
| careful | | other |
| cautious | | other |
| chaotic | | aroused |
| cheerfull | Cheerful | elated |
| chill | Relaxed | calm |
| cocky | | pleased |
| cold | | displeased |
| concentrated | | aroused |
| confidence | confident | pleased |
| confident | | pleased |
| confident excited | Confident | pleased |
| confused | | displeased |
| confused about where to go and what to do | Confused | displeased |
| Content | | pleased |
| Content | Content | pleased |
| Curious | | pleased |
| daydreamy | dreamy | calm |
| dazed | | bothered |
| defeated | | depressed |
| delighted | | elated |
| delighted (not able to associate human emotion) | delighted | elated |
| depressed | | depressed |
| depressed and doubtful | depressed | depressed |
| depressed and sad | depressed | depressed |
| determined | | aroused |
| devious | | displeased |
| disappointed | | displeased |
| disappointed | disappointed | displeased |
| displeased | | displeased |
| dissapointed | | displeased |
| disstressed | distressed | displeased |
| distracted | | other |
| distressed | | bothered |
| dominant | | other |
| doubtfull | Doubtful | displeased |
| down | | depressed |
| dreamy | dreamy | calm |
| dreamy | | calm |
| droopy | | depressed |
| droopy and uninterested | droopy | depressed |
| drunk | | other |
| emotionless | | other |
| empty | | depressed |

| *Original word* | *Changed into* | *Emotion category* |
|---|---|---|
| energetic | | aroused |
| energized | energetic | aroused |
| enjoyed | Pleased | pleased |
| enthousiast | enthusiastic | elated |
| enthusiasm | enthusiastic | elated |
| enthusiastic | | elated |
| excited | | elated |
| exhausted | | depressed |
| fear | Afraid | bothered |
| flustered | | bothered |
| focused | | aroused |
| focussed | Focused | aroused |
| focussed, busy, still quite friendly | focused | aroused |
| forcefully happy (seemed not real) | Happy | elated |
| friendly but focussed | Friendly | pleased |
| friendly, alert (ready for action) | Excited | elated |
| friendly, helpful, little insecure because he is slow | Friendly | pleased |
| frustrated | | displeased |
| frustrated | frustrated | displeased |
| glad | | pleased |
| gloomy | | depressed |
| grumpy | | displeased |
| guilt | Guilty | displeased |
| guilty | | displeased |
| guilty, naughty | guilty | displeased |
| happy | | pleased |
| happy and lively | Happy | pleased |
| happy to be conquering the world | Happy | pleased |
| happy, friendly, active, busy | Happy | pleased |
| happy, friendly, active, calm | Happy | pleased |
| happy, satisfied | Happy | pleased |
| helpful | | elated |
| helpful, confident | Helpful | pleased |
| helpless, insecure, sneaky, creeping .. | Helpless | displeased |
| hesistant | hesitant | other |
| hesitant | | other |
| hesitant and gloomy | Gloomy | depressed |
| hestitant | hesitant | other |
| high | | other |
| hopefull | hopeful | pleased |
| humble | | calm |
| hurried | | aroused |
| hurried, full of itself (overly confi.. | hurried | aroused |
| immersed | | aroused |
| in deep thought | dreamy | calm |

| *Original word* | *Changed into* | *Emotion category* |
|---|---|---|
| industrious | | aroused |
| insecure | | displeased |
| insecure, little angry | insecure | displeased |
| insecure, occupied with own thoughts, busy | insecure | displeased |
| insecure, very sad, as if he got scolded by his mom | sad | depressed |
| intimidating, meant well but still intimidating | Intimidating | aroused |
| it was thinking | dreamy | calm |
| Joyfull | happy | pleased |
| Lazy | | tired |
| Lifeless | | tired |
| little afraid | afraid | bothered |
| little frustrated | Frustrated | displeased |
| Lively | | elated |
| Lost | | depressed |
| lost in thought | Dreamy | calm |
| low and depressed | Depressed | depressed |
| mad | | bothered |
| miserabel | Miserable | displeased |
| miserable | | displeased |
| miserable and stressed | Miserable | displeased |
| motivated | | elated |
| nervous | | bothered |
| neutral | | other |
| neutral, not really something specific | | other |
| not confident | Insecure | displeased |
| offended | | bothered |
| ongeduldig | Impatient | bothered |
| overexcited | Excited | elated |
| overly confident | Confident | pleased |
| overwhelmed | | bothered |
| playful | | elated |
| pleased | | pleased |
| posh (uit de hoogte) | Arrogant | pleased |
| positive | | pleased |
| positive, friendly, ready to help, little too confident | Helpful | pleased |
| preoccupied | | other |
| pride | Proud | pleased |
| proud | | pleased |
| proud (but a bit weird) | Proud | pleased |
| ready | Aroused | pleased |
| relaxed | | calm |
| relieved | | pleased |
| repressive | | bothered |
| robot was slow and, maybe because of that, intimidating. he could be angry and looks like he is going to get you... | Intimidating | aroused |

| *Original word* | *Changed into* | *Emotion category* |
|---|---|---|
| rushed | | aroused |
| rusteloos | Restless | bothered |
| sad | | depressed |
| sadness | Sad | depressed |
| satisfied | | pleased |
| satisfied | Satisfied | pleased |
| satisfied and at ease | Satisfied | pleased |
| scared | | bothered |
| serene | | calm |
| shy | | tired |
| silently angry | Angry | bothered |
| sip | Sad | depressed |
| sleepy | | tired |
| sleepy happy | Relaxed | calm |
| sleepy happy high | Relaxed | calm |
| sleepyness | Sleepy | tired |
| slow | | tired |
| slow and uninterested | Slow | tired |
| sluggish | | tired |
| smug | | pleased |
| statisfied | Satisfied | pleased |
| stressed | | bothered |
| stressed/overthinking | Stressed | bothered |
| strong | | aroused |
| submissive | | depressed |
| surprise | Surprised | aroused |
| surprised | | aroused |
| teleurgesteld | Disappointed | displeased |
| tense | | bothered |
| tensed | Tense | bothered |
| tevreden | Content | pleased |
| thoughtful | | tired |
| timid | | tired |
| tired | | tired |
| tired & sad | sad | depressed |
| uncertain | | other |
| uncomfortable | | displeased |
| unemotional | | other |
| unhappy | | displeased |
| unsure | | other |
| unwilling | | depressed |
| very monotonic and bored | Bored | depressed |
| very sad | Sad | depressed |
| very stressed | Stressed | bothered |
| weak | | tired |

| *Original word* | *Changed into* | *Emotion category* |
|---|---|---|
| worried | | displeased |
| worrying | Worried | displeased |