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A Design Model of Emotional Body Expressions in Non-humanoid Robots

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ABSTRACT

Robotic emotional expressions could benefit social communication between humans and robots, if the cues such expressions contain were to be intelligible to human observers. In this paper, we present a design framework for modelling emotionally expressive robotic movements. The framework combines approach-avoidance with Shape and Effort dimensions, derived from Laban, and makes use of anatomical body planes that are general to both humanoid and non-humanoid body forms. An experimental validation study is reported with 34 participants rating an implementation of five expressive behaviours on a non-humanoid robotic platform. The results demonstrate that such expressions can encode basic emotional information, in that the parameters of the proposed design model can convey the meaning of emotional dimensions of valence, arousal and dominance. The framework thus creates a basis for implementing a set of emotional expressions that are appropriately adapted to contexts of human-robot joint activity.

Author Keywords

Robot emotions, emotional body language, human-robot interaction, non-humanoid robots

INTRODUCTION

Robots are going to work together with people in human-robot teams in the future. In order to work successfully as a team, the members of that team should have a certain level of mutual understanding. Each team member should be able to understand the current status of the other team members: is (s)he successful in what (s)he is doing, does (s)he need help, what his/her intentions are. In human teams, this knowledge often comes from social communication and specific non-verbal behavioural cues, such as emotional expressions. However, in human-robot teams there is a lack of such a communication that often results in failures in jointly performed human-robot activities.

This paper presents a general design framework for expressing artificial emotional states in non-humanoid robots. It focuses on creating a system for designing a specific robotic

body language that could help humans to better understand robot states and intentions in different situations that could occur in a simple working environment.

Previous studies have shown that people can understand emotional states expressed by robots using facial expressions [17, 26]. Less research has been conducted on the possibility of expressing robotic emotions with sounds [24] and body language [3, 15] in humanoid robots. However, very little prior work has addressed the opportunities and challenges of creating an emotionally expressive body language for non-humanoid robots [28, 23].

There exists scepticism among researchers about the ability to reliably identify emotions from the body that has its roots in very early empirical results [13]. So why use bodies and not faces for expressing emotions? Reasons could be numerous [12] based both on a human psychology research and on the specifics of a robotics area.

1. First of all, in spite of the scepticism of recent decades, a number of behavioural experiments showed that recognition performance for bodily expressions is very similar for face and body stimuli [9].

2. Second, a major difference between facial and bodily expressions is that the latter can be recognized from a much bigger distance [31]. This potentially influences the communicative role of facial and bodily expressions, as for example facial expressions could give more information on an internal state of a person while bodily expressions direct attention to a person's actions.

3. Some emotions are more powerfully expressed and easier conveyed using a body than using a face [1]. Some previous studies showed that e.g. when viewing aggressive body pictures, observers spend the most of time looking at hands not faces [18].

4. Finally, it is not clear that robots could or even should have expressive human-like faces. Low and semi-expressive non-humanoid robots can be used more often for home-working tasks (e.g. a robotic vacuum cleaner Roomba), search-and-rescue [4], domestic assistance [33] and other tasks. The design of such robots is intended to match their purpose, e.g. designed to move across disaster zones to find and reach victims, or to be steady and move safely in order to help elderly or disabled people get out of bed and move around. Thus it's not always useful or possible for such robots to have human-like faces. However, it's still useful for them to be able to show expressive cues, as it is a fundamental social signal.

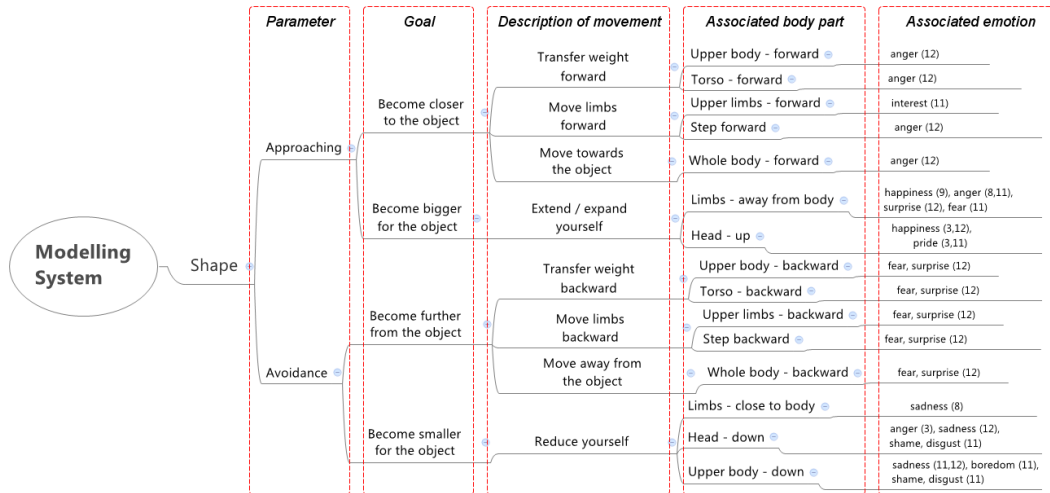| Parameter	Goal	Description of movement	Associated body part	Associated emotion
Approaching	Become closer to the object	Transfer weight forward	Upper body - forward	anger (12)
			Torso - forward	anger (12)
		Move limbs forward	Upper limbs - forward	interest (11)
			Step forward	anger (12)
		Move towards the object	Whole body - forward	anger (12)
	Become bigger for the object	Extend / expand yourself	Limbs - away from body	happiness (9), anger (8,11), surprise (12), fear (11)
			Head - up	happiness (3,12), pride (3,11)
Avoidance	Become further from the object	Transfer weight backward	Upper body - backward	fear, surprise (12)
			Torso - backward	fear, surprise (12)
		Move limbs backward	Upper limbs - backward	fear, surprise (12)
			Step backward	fear, surprise (12)
		Move away from the object	Whole body - backward	fear, surprise (12)
	Become smaller for the object	Reduce yourself	Limbs - close to body	sadness (8)
			Head - down	anger (3), sadness (12), shame, disgust (11)
			Upper body - down	sadness (11,12), boredom (11), shame, disgust (11)

Figure 1. Shape as a category of the emotional modelling system.

In our study we focus on emotional body language for non-humanoid robots. We propose a design framework for modelling emotionally expressive robotic movements. We hypothesize that expressions designed according to the framework help people to recognize five basic emotions implemented in a non-humanoid robot with a better-than-chance recognition level. Previous psychological studies have suggested that the discrete model of basic emotions is not always enough to explain all the complicated nature of an emotional experience [8]. The dimensional approach has been argued to encompass a greater degree of subtlety that supports interpretation of emotional states [8]. In HRI research, a dimensional approach is often used as well for mapping emotional robot's expressions to a specific internal state [25]. In our study we also assume that basic emotions could not explain the whole image of how people see and understand robots. Thus we decided to analyse whether our proposed framework showed any relation between its parameters implemented in a robot and perceived emotional dimensions of valence, arousal and dominance.

The framework presented in our study is an important step in HRI research as it is expected to give other researchers a general design system for fast and easy creation of recognizable emotional expressions in different types of non-humanoid robots.

APPROACH

The expressive behaviours that have been programmed into the robot have been computationally modelled as a simplification of what is known about behaviours that are associated with human and animal emotions. The critical aspect of a robotic emotional signalling system is that the behaviours it generates must be well matched to what is familiar to people. This approach is intended to make a robot's behaviour accessible to the intuitions of a person who observes it. Thus our study focused on perhaps the most fundamental behavioural form of approach-avoidance, which is considered to be a set of universal movements of all animals [2]. Numerous studies have linked approach-avoidance motivations to emotional characteristics [16].

In our study, both approach and avoidance behaviours were analysed from the perspective of a robot's observer. In addition, we employed Laban's body expression theory [19]. Labanian theory, also used in HRI studies [27], classifies elements of expression contained in a body movement into two categories named Shape and Effort, where Shape is a feature that concerns overall posture and movement, while Effort is defined as a quality of the movement.

In order to define the Shape of emotional robot movements, we linked the emotional expression to a more general 'goal' of the expressive robot of either becoming closer to an observer by moving closer or becoming bigger without moving closer, as presented in the Figure 1. These two groups of movements although very different by their nature could both fulfil the purpose of a perspective approach from the observer's point of view and thus communicate a certain emotional cue. In order to generalize the framework of emotional expressions to different types of robots, we linked each possible movement to a specific part of a body in accordance with anatomical body planes that could be applied to both humanoid and non-humanoid bodies. Different features of Shape are organized hierarchically in Figure 1, with the highest level of abstraction on the left and the lowest - on the right. The lowest level of abstraction is a specific emotion associated with higher levels. The emotions are linked to higher level parameters based on previous research in human body language [3, 11, 18, 9, 32].

The Quality was used to capture dynamics of an expressive movement. Quality is divided into three subcategories: energy (strength of the movement), intensity (suddenness), and a flow/regularity category, which is itself subdivided into the duration of the movement, changes in tempo, frequency and trajectory of the movement. Figure 2 presents these subcat-
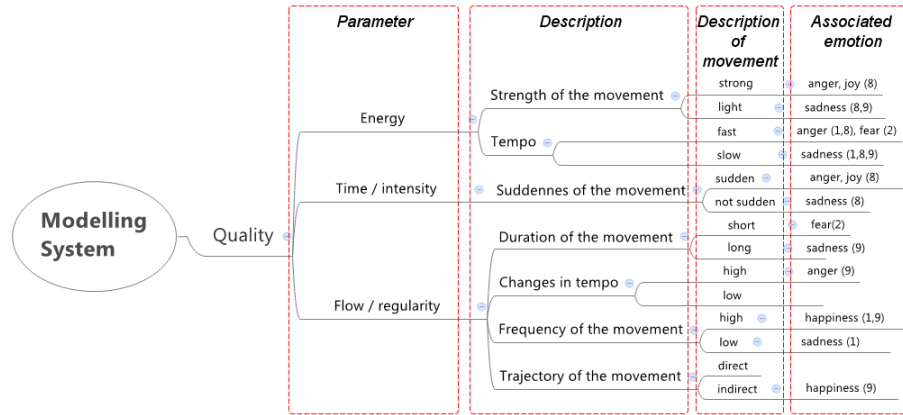
Parameter	Description	Description of movement	Associated emotion
Energy	Strength of the movement	strong	anger, joy (8)
		light	sadness (8,9)
	Tempo	fast	anger (1,8), fear (2)
		slow	sadness (1,8,9)
Time / intensity	Suddennes of the movement	sudden	anger, joy (8)
		not sudden	sadness (8)
	Duration of the movement	short	fear(2)
		long	sadness (9)
Flow / regularity	Changes in tempo	high	anger (9)
		low	
	Frequency of the movement	high	happiness (1,9)
		low	sadness (1)
	Trajectory of the movement	direct	
		indirect	happiness (9)

Figure 2. Quality as a category of the emotional modelling system.

egories as a part of the whole modelling system. Different features representing Quality of the movement are organized in the same hierarchical nature in the Figure 2, as the Shape's categories. The emotions on the lowest level are linked to higher level parameters based on previous research in human body language [15, 11, 18].

METHOD
The robot we have been experimenting with is shown in Figure 3. It was implemented using Lego Mindstorms NXT and was based on a Phobot robot's design [10]. The robot had two motors that allowed it 1) to move forward and/or backwards on the surface, 2) to move its upper body part. The upper body part was constructed in such a way that the robot's hands were connected and moved together with robot's neck and eyebrows. Neck could move forward / backwards, hands could move up and down, and eyebrows could also rise up and down.

Figure 3. Lego robot used in the studies.

For programming robot's behaviours the RWTH – Mindstorms NXT Toolbox for MATLAB [1] was used. This software is a free open source product and is subject to the GPL. The RWTH toolbox was developed to control Lego Mindstorms NXT robots with Matlab via a wireless Bluetooth connection or via USB.

Use of Framework for Expressing Basic Emotions

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[1] **http://www.mindstorms.rwth-aachen.de/**

Our first research question was formulated as follows: Do expressions designed according to the framework help people to understand five basic emotions implemented in a non-humanoid robot with a better than chance recognition level?

The independent variable here is the emotional expression presented by the robot. In our study we used five emotional expressions: afraid, angry, happy, sad and surprised. We also implemented a control expression with no emotion when a robot doesn't react affectively to a change of the environment. The dependent variable was an emotional term, selected by participants and based on their recognition of the expressed emotion. We offered participants seven terms to select from: afraid, angry, happy, sad, surprised, not emotional, other. The measure used to obtain results for this research question was the recognition ratio $r(p_i, e_j)$ for each expression, which was calculated as defined by Eq. 1.

$$r(p_i, e_j) = \frac{N_{ij}}{N} \qquad (1)$$

where p_i = expression number i , e_j = selected emotional code number j; N_{ij} = number of responses (p_i, e_j); N = total number of respondents.

Model's Parameters and Emotional Dimensions
We used an experimental study to investigate the causal relations between the parameters affective robotic expressions and a perceived emotional dimension. Due to the limitations of a robotic platform, not all the parameters of the model were implemented in our experiment. We implemented the following parameters in five affective expressions and one neutral:

1. Approach/avoidance parameter. This parameter was defined as +1 for approaching movements, -1 for avoidance and 0 for none.

2. Energy/speed parameter, defined as an average power of robot's motors per expression, where 100 (%) is a maximum.

EmotionID	Approaching / Avoidance	Energy	Intensity	Duration, sec	Frequency
1 (afraid)	-1	100	1	0.63	1.59
2 (angry)	1	75	1	2.58	0.78
3 (happy)	1	67	1	3.33	0.60
4 (sad)	mixed, not used in analysis	27	0	12.0	0.17
5 (surprised)	-1	75	1	1.0	1.00
6 (not emotional)	0	0	0	0.0	0.00

Table 1. Defining the main parameters of the framework.

EmotionID	Description	Valence / Pleasure	Arousal	Dominance
1	afraid	-1	+1	-2
2	angry	-1	+1	+2
3	happy	+2	+1	+1
4	sad	-2	-2	-1
5	surprised	0	+2	0
6	not emotional	0	0	0

Table 2. Mapping between discrete emotions and three emotional dimensions.

Context	Recorded emotional expression
Valence positive / negative	Happy, angry, neutral
Arousal positive / negative	Sad, surprised, neutral
Dominance positive / negative	Angry, afraid, neutral
Neutral	Afraid, angry, happy, sad, surprised

Table 4. A list of emotional expressions, presented to participants.

3. Time/intensity parameter, defined as +1 when robot's expressive movements were programmed as sudden (Motors.SmoothStart = false) , and as 0 when the movements were programmed as smooth (Motors.SmoothStart = true).

4. Flow/regularity parameter, consisted of two sub-parameters:

   (a) Duration of the expression

   (b) Frequency of movement, defined as Number of hands' movements / Duration

For each of the expressions the values of parameters presented in Table 1 were used as independent variables.

The values of recognized valence, arousal and dominance were used as dependent variables in our study. We used a Mehrabian model of emotions [20] to present five basic discrete emotions used in our study to a three-dimensional pleasure-arousal-dominance (PAD) space. We decided to use the PAD model firstly because it is often used to measure the affective value of facial expressions, and second because there was a validated questionnaire available.

The mapping between discrete emotions and the three dimensions was conducted based on previous studies in behavioural and experimental psychology [6, 14] and is presented in the Table 2. We scaled the values of all three dimensions to a 5-point scale [-2, 2] in order to proportion it to a 5-step Self-Assessment Manikin tool [5] we used for measuring participants' perception.

Creating Context

We used the same three-dimensional approach for creating a context for robot emotional expressions, as described in Table 3 .

As a result, we recorded a set of videos where each context was combined with a specific emotional expression of the same and the opposite level of the appropriate dimension.

As a consequence, we got a list of twenty three emotional expressions of the robot in different contexts, as described in Table 4, each of the duration of about 5 sec.

A within-subject design was used to assign participants to a specific task condition, i.e. each participant was exposed to all the experimental conditions. In order to overcome limitations of a within-subject design and decrease the impact of a learning effect, the videos presented to each participant were randomized. We used a site http://www.random.org to randomize the conditions and ensured the two expressions of the same emotion were never presented one after another.

Participants were initially given a questionnaire containing demographic questions about age and gender, and the Toronto Empathy Questionnaire [30]. The participants were asked to sit on a chair at the table in a quiet room, watch the recorded videos and after each of them answer the questions from the prepared paper-based questionnaire. The questionnaire contained a Self-Assessment Manikin tool [5] and a forced-choice question regarding the perceived emotion of the robot. In order to produce reliable results we tried to eliminate and control biases that could appear during the experiment. In order to control biases, we prepared a written document with detailed instructions for participants and ran a pilot study before actual data collection to identify potential biases. In order to control biases caused by participants, we created task procedure that caused the least stress to the users and reassured the participants that we were testing the robot's behaviour, not them. The experimenter stayed neutral while supervising experiments thus reducing the chance to intentionally or unintentionally influence the experiment results. We controlled environment-introduced biases by making the experimental room without notable distractions. The participant was seated alone at the table and the experimenter was seating in another corner of the room in case the participant would need any help. The duration of the experiment didn't exceed thirty minutes.

One-way repeated measures ANOVA was used as a statistical test for evaluating the relation between each parameter and

Dimension of a context	Positive	Negative	Neutral
Valence	Something positive happens, e.g. robot finishes its task successfully.	Something negative happens due to e.g. robot's fault.	Nothing happens.
Arousal	Something sudden happens in the environment.	Nothing happens in the environment, robot's help isn't needed.	Nothing happens.
Dominance	Robot has no power to handle a situation as something dangerous prevents it from completing a task, e.g. a big obstacle.	Robot has a power to handle a situation as something harmless prevents it from completing a task, e.g. a small obstacle.	Nothing happens.

Table 3. Dimensional approach for creating a context for robot emotional expressions.

Expressed emotion	Recognition within appropriate context	Recognition within inappropriate context	Recognition without context
afraid	59%	35%	44%
angry	59%	48%	38%
happy	100%	34%	50%
surprised	88%	47%	47%
sad	12%	12%	9%

Table 5. Recognition ratios for presented expressions.

a perceived emotional dimension. The G*Power tool [2] was used to compute statistical power analyses for this test and an a priori calculation of a required sample size showed the need of 33 participants for our within-subject study in order to have an Effect size f= 0.3 (where err prob=0.05, Power (1- err prob)=0.95, Number of groups = 3).

RESULTS
34 people (9 females, 24 males and 1 prefered not to say) agreed to participate in a study, ranging in age from 18 to 46 (M=23.21, SD=7.42).

Recognition ratio
The values of recognition ratio for each presented expression are given in the Table 5. The recognition ratio for such emotions as surprise and happiness were the highest within an appropriate context (88% and 100% respectively). The lowest recognition ratio was for the emotion of sadness, as shown in the Table 5. An appropriate context added to an emotional expression increased the recognition rate for all the emotions, with the difference between an appropriate context and a context-neutral expression to range between 3 and 50%.

Modelling Parameters: Approach and Avoidance
We used a repeated measures ANOVA test for investigating a relation between different parameters of emotional robot expressions and a value of perceived valence, arousal and dominance. This test with a Greenhouse-Geisser correction didn't reveal any significant difference between the perception of arousal, although both approach and avoidance significantly (p<.0005) increased the perceived level of arousal comparing to a neutral robot expression. Mean scores of valence differed significantly between a neutral expression, approach and avoidance (F(1.74,57.49) = 32.399, p<.0005). The mean score of valence for the expression of avoidance was negative

and was significantly lower (p<.0005) comparing it to a positive mean of valence for approach or to a neutral expression. Mean scores of dominance also differed significantly between a neutral expression, approach and avoidance (F(1.75,57.68) = 3.76, p=.035). Approach expressions determined a significantly higher positive value of a perception of dominance, avoidance a significantly lower negative value (p=.011).

We analysed an influence of different contexts on the perception of valence, arousal or dominance of an expression. The results of a repeated measures ANOVA with a Greenhouse-Geisser correction showed that positive valence of a context significantly increased (p<.05) a perceived level of valence of robot's expression, comparing to other contexts. At the same time, positive valence of a context significantly (p<.0005) increased a perceived dominance of expressions. Negative arousal of a context significantly decreased (p<.05) a perception of arousal of an expression, although positive arousal didn't have any significant influence.

Modelling Parameters: Energy
A repeated measures ANOVA with a Greenhouse-Geisser correction revealed that the mean scores of valence for different energy levels differed statistically significantly (F(2.73,90.16) = 16.02, p<.0005), the same as the mean scores of dominance (F(2.19,72.58) = 9.94, p<.0005) and arousal (F(2.31,76.25) = 80.45, p<.0005). Expressions implemented with a high energy statistically significantly reduced the valence and dominance perception comparing to both a medium energy (p<.0005), low energy (p=.002 for valence and p=.038 for dominance) and a neutral expression (p<.0005 for valence and p=.022 for dominance). Therefore, we can conclude that a high energy of expression elicits a statistically significant reduction in the perception of valence and dominance. At the same time, higher speed representing higher energy of expressions significantly increased perceived arousal when changing from low to medium (p<.0005) and from medium to high level (p=.014).

Modelling Parameters: Intensity
A repeated measures ANOVA test with a Greenhouse-Geisser correction didn't find any statistically significant difference of perceived valence (F(1.00,33.00)=.28, p=.60) or dominance (F(1.00,33.00)=2.07, p=.16) between different intensity levels. However, higher intensity determined a significant increase in arousal perception of expression (F(1.00,33.00)=154.94, p<.0005).

Modelling Parameters: Duration

Regarding a duration of robot expressions, a repeated measures ANOVA with a Greenhouse-Geisser correction revealed a statistically significant difference in perception of both valence ($F(2.72, 89.74)=6.4$, $p<.005$), arousal ($F(2.54, 83.87)=72.893$, $p<.0005$) and dominance ($F(2.23, 73.51)=11.0$, $p<.0005$). Valence perceived for the expression with a short duration (up to 1 sec) was significantly lower ($p=.003$) than valence of the expressions of a longer duration (2 to 3.3 sec). Low and medium duration of expressions (positive up to 3.3 sec) was perceived with a significantly ($p<.0005$) higher arousal level than a long duration of an expression (12 sec). However, any positive duration significantly ($p<.0005$) increased a perceived arousal score comparing to a neutral expression, which caused a negative arousal perception. Medium duration of expression caused a significantly ($p<.05$) higher perceived dominance level than low or high levels of expression's duration.

Modelling Parameters: Frequency

A repeated measures ANOVA with a Greenhouse-Geisser correction revealed a statistically significant difference in perception of both valence ($F(2.73, 90.16)=16.02$, $p<.005$), arousal ($F(2.31, 76.25)=80.45$, $p<.0005$) and dominance ($F(2.20, 72.58)=9.94$, $p<.0005$) for different frequency levels. Valence perceived for the expression with a high frequency (1.6 movement/sec) is significantly lower ($p<.005$) than any other level of frequency (0-1 movement/sec). Any increase in frequency rate significantly increases ($p<.05$) a perception of expression's arousal. Both low and high frequency of emotional expressions corresponds to a negative dominance, which is significantly different ($p<.05$) from a positive perceived dominance of an expression of a medium frequency.

DISCUSSION

We proposed a framework for expressing and interpreting emotional movements in non-humanoid robots that is based on a behavioural form of approach-avoidance analyzed from an observer's point of view and the Labanian theory of movement analysis. We implemented the expressions of five basic emotions into a non-humanoid Lego robot. Let us examine how the study answered our research questions.

1. Do expressions designed according to the framework help people to understand five basic emotions implemented in a non-humanoid robot with a better than chance recognition level?

The results of the performed study showed that the values of recognition ratio exceeded the chance level for four recognized emotions: fear, anger, happiness and surprise. The recognition ratio for the emotion of sadness was lower than a chance level, so we can conclude that this specific emotional expression was not recognized correctly by the subjects. The reasons could be explained by comparing the current results with the results of several previous studies.

Table 6 compares the results of a recognition ratio within an appropriate context with the results of the similar previous experiments, where 1) the same robot expressed emotions in a dynamic way without a context [22], 2) the same robot expressed emotions in a static way without a context [21], 3)

Expressed emotion	Current study, appropriate context	Same robot, dynamic expressions, no context	Same robot, static images	Feelix	Eddie
afraid	59%	68%	42%	16%	42%
angry	59%	36%	15%	40%	54%
happy	100%	32%	36%	60%	58%
surprised	88%	57%	52%	37%	75%
sad	12%	14%	41%	70%	58%

Table 6. Comparison of our results with the results of the similar previous experiments.

70-cm tall Lego robot Feelix expressed emotions using facial features [7], 4) 23 DoF robot EDDIE expressed emotions using facial features and some animal-inspired attributes [29].

The recognition ratio for anger, happiness and surprise in our study were higher comparing to all previous experiments, as presented in the Table 6. The recognition ratio of fear in our study was higher than that of the studies with Feelix, Eddie and static pictures of the same robot, although lower than our previous study with dynamic robot expressions. The only difference in the current expression of fear with the previous study is the existence of a context. Thus we could suggest that either a context for this expression was not chosen correctly, or the expression of fear is better recognized without any specific context. More experiments should be performed with this robotic expression in different contexts and without it in order to prove any of these hypotheses.

The recognition ratio of sadness was extremely low in our current study and hasn't even reached the chance level. However, a comparison with previous experiments suggests that the emotion of sadness is much better recognized from facial cues, as with Eddie and Feelix robots. On the other hand, a static picture of the expression of sadness is recognized with a significantly higher ratio than a dynamic expression. Earlier in this paper we have mentioned that some emotions are easier conveyed using a body than using a face [1]. Our results suggest that the emotion of sadness is the one which is expressed more powerfully using static facial feature and not the dynamic body language. If we focus on the specific features of the expression of sadness, we can notice that it is often described as slow, long movements of a low frequency, when limbs and head are kept close to the body, not moving. All this shows the intention to be as non-dynamic as possible during the expression of sadness. That's why, probably, the static picture represents sadness much better than any dynamic expression. However, more experiments need to be performed in order to prove this hypothesis.

In general, the results show that for such an emotional state as sadness a static facial expression fits more than dynamic bodily emotional expressions. Other emotions, especially surprise and happiness, can be expressed using a body language at least as successfully as facial features, and often even more successfully.

2. What is the relation between our framework's parameters and the recognized dimensions of valence, arousal and dominance?

The results of the study support our basic claim: the parameters of the design framework can be used as a model for implementation in a non-humanoid robot so that they can be related to perceived levels of valence, arousal and dominance. The design framework is conceptual tool that combines three dimensions of approach-avoidance, Shape and Effort. The model defines an architectural relationship between these ideas, bridging the framework and the implementation.

Arousal, according to the result of the study, was increased by both approach and avoidance behaviours, high intensity or an increase of speed of an expression, as well as an increase of frequency of limbs' movements. Decreased arousal, on the other hand, was related to a short or medium duration of an expression, low intensity and a context of a negative arousal.

The results show that it is easier to decrease a perceived valence of an expression by making it of a short duration or high speed, by increasing the frequency of limb movements to a high level, or by expressing avoidance. All the parameters mentioned make valence negative. In order to increase a perceived valence, an expression needs to be tied to a context of positive valence. An expression of approach increases a perceived valence and makes it positive.

Changing a perception of dominance by controlling parameters of our design model is similar to changing the perception of valence. As with valence, high speed of expression, high frequency of limb movements and avoidance all decrease the level of perceived dominance and make it negative (i.e. subjugated). Also as with valence, a context of positive valence tied to an expression increases the level of perceived dominance. However, the situation is different with a parameter of a duration of an expression: a medium duration of an expression increases the level of dominance and makes it positive, contrasting with duration's influence on valence.

In general, these results conform to a certain degree to what was shown by previous research that linked e.g. strong, jerk and intensive approaching movements to anger [11, 18, 9, 32], or linked a short and fast movements together with an avoidance behaviour to fear [15, 9]. Such a correspondence is suggested by making one more step and associating e.g. anger with a negative valence, high arousal and high dominance, while fear can be associated with a negative valence, high arousal and low dominance. However, such a link is not straightforward and is sometimes arguable. Our results however expand previous work by showing a direct link between the parameters of our suggested design framework and all the three emotional dimensions. Such a broader and more detailed model can help the researchers in implementing a broad range of emotions into non-humanoid robots.

CONCLUSION

This paper has presented research concerning the capacity for creating behavioural expressions of artificial emotions in human-robot interaction. As in human-human non-verbal social communication, expressive movements of the body play an important role in HRI. The goal of this research was to present and validate a general design framework for expressing artificial emotional states in non-humanoid robots. We proposed a design framework for modelling emotionally expressive robotic movements.

We posed two main research questions: Do expressions designed according to the proposed framework help people to understand five basic emotions implemented in a non-humanoid robot? What is the relation between our framework's parameters and the emotional dimensions recognized by human observers? We investigated these questions using an exploratory study, where participants observed different expressions implemented in a non-humanoid robot according to the proposed design framework.

The results from this study demonstrate that the emotions of fear, anger, happiness and surprise are recognized on a better-than-chance level when implemented according to our proposed framework and expressed by a non-humanoid robot within an appropriate context. The results suggest that the emotion of sadness is more powerfully expressed using static facial features, not by dynamic body language. In addition, our results show that the parameters of our suggested model are related to the perceived level of valence, arousal and dominance. Thus, our model can be used by HRI researchers as a basis for implementing of a set of emotions in non-humanoid robots. It's important to consider the context of joint human-robot activity when deciding how to map from the VAD dimensional space into the behavioural space. The activity context will condition a person's ability to infer the meaning of a robot's behaviour: it cannot be understood in isolation from the task it is performing, or the human-robot joint activity in which it is engaged.

Future work will test the proposed design framework with other types of non-humanoid robots, as well as with humanoid robots. We also plan to analyse an effect of expressing artificial emotion on the efficiency of a joint human-robot activity.

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