2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)

Robots Expressing Dominance: Effects of Behaviours and Modulation

1st Rifca Peters
Intelligent Systems
Delft University of Technology
Delft, The Netherlands
r.m.peters@tudelft.nl

2nd Joost Broekens
LIACS
Leiden University
Leiden, The Netherlands
joost.broekens@gmail.com

3rd Kangqi Li
Intelligent Systems
Delft University of Technology
Delft, The Netherlands
likangqi7893@gmail.com

4th Mark A. Neerincx
Intelligent Systems
Delft University of Technology
Delft, The Netherlands
m.a.neerincx@tudelft.nl

***Abstract*—A mayor challenge in human-robot interaction and collaboration is the synthesis of non-verbal behaviour for the expression of social signals. Appropriate perception and expression of dominance (verticality) in non-verbal behaviour is essential for social interaction. In this paper, we present our work on algorithmic modulation of robot bodily movement to express varying degrees of dominance. We developed a parameter-based model for head tilt and body expansiveness. This model was applied to a variety of behaviours. These behaviours were evaluated by human observers in two different studies with respectively static pictures of key postures (N=772) and real-time gestures (N=31). Overall, specific behaviours proved to communicate different levels of dominance. Further, modulation of body expansiveness and head tilt robustly influenced perceived dominance independent of specific behaviours and observer viewing height and angle. The modulation did not influence perceived valence, but it did influence perceived arousal. Our study shows that dominance can be reliably expressed by both selection of specific behaviours and modulation of behaviours.**

***Index Terms*—Human-robot Interaction, Social Robotics, Body Language, Dominance, Power, Non-verbal Behaviour, Expression, Social Signal Processing, Perception, Synthesis, Modulation**

I. Introduction

Robots and virtual agents increasingly fulfil functions that require social interaction and communication with people who are not trained to interact with a robot or avatar. In inter-human communication, the interaction consists of both verbal and nonverbal behaviour. Nonverbal behaviour conveys information about the relationship and about likes and dislikes [1]. Based on observable behaviours (e.g., facial expression, proximity) people form impressions of the others and develop expectations [2]. For artificial agents (both virtual and robotic), to engage in meaningful interactions with humans, the importance of social intelligence is widely acknowledged [3], [4].

Research on emotional expressions for virtual agents is abundant (e.g., [5]–[7]). A common approach for the design of emotional expressions is to develop specific behaviours based on human emotion expression in a particular modality (e.g., posture, gesture, gaze, facial expressions) [3]. Facial expressions are considered important cues for emotions [8], but variations in appearance and functionality of robots as well as line of sight of the user poses limitations on the usefulness of this modality. Emotional expressions are possible with body posture as well; Cohen [9] reported high recognition rates for the emotional expressions of a "facial robot" (iCAT) and a "bodily robot" (NAO). Further, expressing affect *while the robot is busy with its task* (sometimes referred to as mood expression [10]) can be useful in interaction scenarios where the robot is observed by the user while performing a task. Therefore, alternative models for affect expression are needed.

Alternative models for different types of robots have been investigated. For example, Lin [11] applied transformations to walking motions of a virtual avatar and showed that discrete emotions can be expressed by manipulating motion stiffness, pace, and expansiveness. Beck [12] attempted to create an 'affect space' able to express emotions on the two dimensional circumplex model of affect [13] by blending key poses of discrete emotions. Xu [14] defined behaviour-specific design patterns of key poses and interpolation parameters targeting specific joints, which showed able to express valence and arousal [15].

We focus on three challenges in affect expression. First, most models and methods require a considerable amount of work in the form of key poses or interpolation patterns for each behaviour before being usable. Second, it is important to assess perceived affect by the users on the affective dimension that is intended to be manipulated, in other words, we need a validated set of "stimuli". Third, most models of affect expression focus on valence and arousal, or, discrete emotions.

In this paper, we present our work on algorithmic modulation of robot bodily movement to express varying degrees of dominance. We developed a parameter-based model for head tilt and body expansiveness. This model was applied to a variety of behaviours and user view angles. These behaviours were evaluated by human observers in two different studies with respectively static pictures of key postures (N=772) an real-time gestures (N=31).

II. Dominance

Humans (unconsciously) use social signals to inform others about their affective stance or attitude; based on observations we evaluate someone as, among other things, warm or cold, friendly or hostile, and dominant or submissive (e.g., [16], [17]). Body language serves various communicative functions,

This work is funded by the EU Horizon 2020 PAL project (grant nr. 643783).

amongst which affect displays [18]. It is commonly accepted that power or status, i.e., dominance, is an important factor in interpersonal relations and communications. Dominance is defined as "power and influence over others" [19], but research fields adopt specific notions.

Dominance is a factor in the interpersonal circumplex —or Leary's Rose— a two dimensional model for interaction stance defined by: dominance–submissiveness and affiliation–hostility [20], [21]. Dominance, in this view, is an interpersonal factor. Further, the complementary mechanism enables strategic use of dominance display as a tool to form interactions by, for example, teachers [22] and police officers [23]. In social signal processing the dominance dimension is referred to as *verticality* [24].

Dominance is also a dimension of affect [1], [25]. Suggested is that affect (including discrete emotions, moods, and attitudes) can be placed in a multidimensional pleasure, arousal and dominance (PAD) model [26]. Emotions are directed responses to internal and external events [27], and can be either self-directed or social. Thus, a dominance relation can exist between a person and the environment or a stimulus as well. Dominance reflects the amount of influence, power and overwhelmingness of a stimulus, be that another human or a magnificent forest.

Both notions of dominance, dominance-as-emotion-dimension and verticality-as-social-stance, relate to similar concepts such as power, control and influence. They are both relational. The first is defined as an affective dimension, and thus has meaning in the context of affect communication. The second is defined as a interpersonal dimension and has meaning in the context of relations. However, both share similar behavioural cues for expression. Therefore, for the purpose of expressing dominance/verticality through the body language of a robot, we propose to consider these dimensions to be equal.

A. Dominance Expression in Humans

Body shape, or posture, has been associated with dominance display. A dominant posture was stereotyped as forward [28], open [28]–[30], expansive [30], upright [28], and oriented towards the other [28]. Various studies reported a positive influence of body expansiveness and/or openness on dominance expression (e.g., [30], [30], [31]). Carney [30] defined openness as "keeping limbs open or closed", and expansiveness as "taking up more space or less space", but other authors provided less clear definitions of the terms or used them intertwined. In the remainder of this paper *expansiveness* is used to indicate both similar features.

However, the relation between posture and dominance is arguably moderated by other factors such as gender or culture [32], and supposedly previous work was inconclusive, based on limited data, or highly context dependent [29]. Moreover, most studies used pre-recorded exemplary images and compared between distinctive postures. Meaning that the results are only valid for the specific posture under evaluation.

Gestures, co-verbal motions of arms and/or head, are also an important cue for dominance expression. Though, frequency and types are discussed rather than performance. Exception is Kipp [33] who found that an open hand shape is associated with submissiveness while a pointing hand shape is associated with dominance. However, this may result from the sign function of both gestures (pointing at someone vs holding your hands to receive something), and as such does not have to do with modulation of openness.

Pointing was repeatedly associated with dominance expression [34]–[36]. Pointing is believed a signal of aggression, anger, or arrogance —emotions with a high dominance value in the PAD model [35]. Other types of gestures were associated with dominance as well for there aggressive (e.g., [35]) or attention gaining (e.g., [37]) feature. Head position has received specific attention, multiple studies unanimously concluded that upward head tilt is associated with dominance [28], [38], [39].

To summarise, key poses, head tilt, and body expansiveness are widely acknowledged bodily cues for expressions of dominance/submissiveness. However, concrete models for dominance expression are unavailable.

B. Dominance Expression in Conversational Agents

There is growing interest in synthesis of expressive behaviour for virtual agents and robots. Often however, studies are application specific and evaluate pre-designed behaviours, often mirroring human behaviour, rather than parameter-based models (e.g., [5], [40], [41]).

Nonetheless, models for dominance expression were subject of research before. Studies may focus on behaviour selection (e.g., [42]), but this line of work gives no insight on the features of the behaviours that convey the signal. It may indicate which behaviours are appropriate, but not how these behaviours should be performed. Study on the 'manner' of performance was done by, for example, Lance [43]. Reportedly, gaze behaviours expressing dominance are performed with head tilted up and a higher body compared to submission. This study, like others, used specific (gaze) behaviours, the effect for other behaviours remains unknown. Ravenet [44] combined behaviour (type) selection and gesture performance parameters (i.e., power, amplitude). They obtained, from co-design, parameters for dominance display similar to studies in human behaviour which served as input to model avatar behaviour. However, validation of this model was not presented. A recent study did perform an exhaustive analysis of valence and arousal perception of gestures and performance parameters and found interesting interaction effects between gestures and performance [45].

Studies that evaluate parameter-based models to control dominance expression often modify multiple parameters in parallel (e.g., [46], [47]). This approach makes it impossible to derive the effect of unique parameters, and thereby hard to reuse. Evaluation of unique parameters is laborious and results seem context dependent. For example, while Kim [48] reported a positive effect on dominance expression for direction and speed, Saerbeck [49] reported a positive effect for motion direction and a negative effect for motion speed.

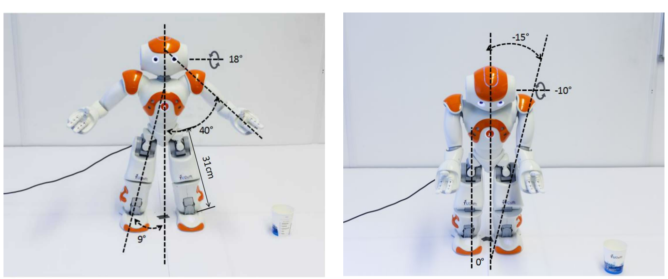
So far, dominance was found positively correlated with forward sagittal motion direction [48], [49], forward gaze direction [40], head position tilted upward [40], [43], and gesture direction [48], [49]. Results for gesture speed were inconclusive [48], [49].

Because it is currently unknown how dominance perception can be manipulated using specific behavioural parameters, in this work we focus on a detailed study to identify the effect of body expansiveness (head tilt as a part of expansiveness) on perceived dominance. We try to isolate the effect of expansiveness but test this on a range of behaviours and user viewing angles to ensure that the effects we find are generic. We also identify the effect of the behaviours themselves on perceived dominance, as a possible confound but also as a means to express dominance.

III. Robot Dominance Model

Based on behavioural cues for dominance expression in human-human interaction (see Section II), we developed a parametric model of body expansiveness for dominance expression in a humanoid robot. We selected five parameters manipulating body expansiveness: vertical head angle, horizontal shoulder angle, horizontal and sagittal hip angle, and vertical leg stretch (Fig. 1).

The modulations are applied to existing (neutral) NAO behaviours. We define a factor f as the dominance level which is positively correlated with the dominance expression, and ranging $[-1.00, 1.00]$, where 0 is the neutral stance, and -1 and 1 represent the most submissive and the most dominant stance respectively. Based on the f value the movement trajectory of affected joints is adapted. For head and arm movement a linear modulation between the neutral and limit position (see Table I) is executed on joints `HeadPitch`, `LShoulderRoll`, and `RSholderRoll`. A time adjustment is applied to maintain a consistent speed. The legs are adapted



(a) dominance

(b) submissiveness

Fig. 1: example manipulations for the most dominant and most submissive stance as implemented on the NAO robot in a standing position. Maximum dominance: head tilt 18°, arm spread 40°, leg spread 9°, and leg stretch 30cm (Fig. 1a). Maximum submissiveness: head tilt -10°, arms enclosing 10°, leg angle 0°, and leg stretch 26.5cm (Fig. 1b).

accordingly following one of three standing patterns (i.e., neutral, dominant, submissive).

Although the following implementation is NAO specific, the principles explained therein can be used on any humanoid with a similar structure.

A. Implementation

We implemented the parameter-based model for dominance expression in an existing framework for NAO behaviour management. To execute a behaviour on the NAO robot, it expects two arrays with the path and execution time for the behaviour. The path information for all original (neutral) behaviours is stored in an XML file. To manipulate dominance expression we apply joint modulations relative to the neutral path and based on the dominance level. The affected joints and their adjustment patterns are given in Table I.

a) Motion Trajectory: For a specific behaviour, multiple joints are moving in parallel. The path of joint i is described as:

$$\begin{Bmatrix} x_i = & (x_{i0}, x_{i1}, \cdots, x_{in_i}) \\ t_i = & (t_{i0}, t_{i1}, \cdots, t_{in_i}) \end{Bmatrix} \quad (1)$$

where x_{ij} is the trajectory value of joint i at t_{ij} time, and n is the maximum value of n for all m joints. The path for the entire behaviour can be described as two $m \times n$ matrices: $X_{m \times n}$ and $T_{m \times n}$.

b) Parameter Insertion: For each k modulated joints, an array will be inserted in the path matrix. If we define the inserted arrays as $N_{k \times n}$ and $L_{k \times n}$, the path matrix will be:

$$X'_{(m+k)\times n} = \begin{pmatrix} X_{m\times n} \\ Y_{k\times n} \end{pmatrix}, T'_{(m+k)\times n} = \begin{pmatrix} T_{m\times n} \\ L_{k\times n} \end{pmatrix} \quad (2)$$

Non modulated joint movement remains the point-to-point path specified in the XML file.

c) Head and Arm Movement: Linear modulation is applied to the path trajectories of selected joints (i.e., `HeadPitch`, `LShoulderRoll`, and `RShoulderRoll`) as follows:

$$J(f) = \begin{cases} x_{Neutral} + (x_{Max} - x_{Neutral}) \times f & , f > 0 \\ x_{Neutral} - (x_{Neutral} - x_{Min}) \times f & , f < 0 \end{cases} \quad (3)$$

TABLE I: modulated joints, and joint angle values for most dominant, neutral and most submissive stance. (Left joint values are given, right joint values were reflected.)

Parameter	**Joint**	**Dom**	**Neutral**	**Sub**
Head tilt	`HeadPitch`	0.51	0.00	0.67
Shoulder angle	`LShoulderRoll`	1.33	0.00	-0.31
Leg angle	`LHipYawPitch` `LHipRoll`	-0.17 0.09	0.00 0.00	0.00 0.00
Leg stretch	`LHipPitch` `LKneePitch`	0.13 -0.08	0.00 0.00	-0.44 0.69
Stability correction	`LAnklePitch` `LAnkleRoll`	0.08 -0.13	0.00 0.00	-0.35 0.00

x_{Max} and x_{Min} are the reference values for the limit positions (i.e., most dominant and submissive), corresponding with the joint angles listed in Table I. The dominance factor f is the relative proportion of modulation applied between the neutral and limit position.

We define the three modulated joints as $x_0 \sim x_2$, from (3), their new trajectory is derived as:

$$x'_i = (J(x_{i0}, f), J(x_{i0}, f), \cdots, J(x_{in}, f)) \tag{4}$$

Let

$$X_1 = (x'_0, x'_1, x'_2)^T \tag{5}$$

X_1 is the first three rows of the trajectory matrix.

d) Time Adjustment: A time-stamp adjustment is applied to maintain the velocity and acceleration over shortened or prolonged trajectories. For a positive factor f the time is increased. To increase time by the same portion as the trajectory the percentage increase for each time interval should be the same as the percentage increase of the trajectory. From (3) we can get:

$$\begin{aligned} x'_{ij} &= x_{ij} + (x_{max} - x_{ij}) \times f \\ x'_{i(j-1)} &= x_{i(j-1)} + \left(x_{max} - x_{i(j-1)}\right) \times f \end{aligned} \tag{6}$$

Then we get the angle displacement:

$$x'_{ij} - x'_{i(j-1)} = (x_{ij} - x_{i(j-1)}) \times (1 - f) \tag{7}$$

The change in proportion $\frac{x'_{ij} - x'_{i(j-1)}}{x_{ij} - x_{i(j-1)}}$ will be $(1 - f)$. Therefore, the new j time for joint i is calculated by:

$$t'_{ij} = t'_{i(j-1)} + \left(t_{ij} - t_{i(j-i)}\right) \times (1.00 - f) \tag{8}$$

e) Leg Movement: We created three patterns of standing poses that vary in expansiveness and extension instead of continuous path trajectories due to balance constraints. The patterns were created manually, and relate to the dominance factor as follows:

$$SPattern(f) = \begin{cases} Pattern_{sub} & , -1.00 \le f < -0.33 \\ Pattern_{neu} & , -0.33 \le f \le 0.33 \\ Pattern_{dom} & , 0.33 < f \le 1.00 \end{cases} \tag{9}$$

Upon change of dominant factor f above the specified thresholds, a transition between standing patterns takes place in parallel with behaviour execution. Assume the 3rd to 12th rows in X' and T' are the path for the legs joints, then these values will be replaced by those of the new leg pattern. These new values are defined as two $10 \times n$ matrices X_2 and T_2. The final path for this behaviour is:

$$X'' = \begin{pmatrix} X_1 \\ X_2 \\ X_r \end{pmatrix}, T'' = \begin{pmatrix} T_1 \\ T_2 \\ T_r \end{pmatrix} \tag{10}$$

X_r and T_r are paths of unchanged joints.

IV. Pilot: Model Validation

A. Method

We conducted a 2 (expansiveness) x 2 (horizontal angle) x 2 (vertical angle) between-subject, factorial posture perception study to evaluate the effect of body expansiveness on perceived dominance expression and explore covariates view angle.

a) Stimuli: The expansiveness modulation described in Section III was applied to 11 distinctive postures performed by a NAO robot. Pictures were taken from a 0° and 30° horizontal angle and with the robot standing on ground level and a 110cm height table.

b) Measurement: Perceived dominance of the stimulus was measured on a 5-point Likert scale (dominant to submissive).

c) Procedure: An on-line survey was set-up at Amazon Mechanical Turk. A Human Intelligence Task (HIT) consisted of 11 subsequent pictures presented in random order and depicting postures within one condition. A HIT could be started anytime. Each participant could complete the HIT only once. First, demographic data was collected and the task was explained. Then, two trail questions were presented, showing iconic human expressions of dominance and submissiveness. Finally, participants rated the robot images one by one.

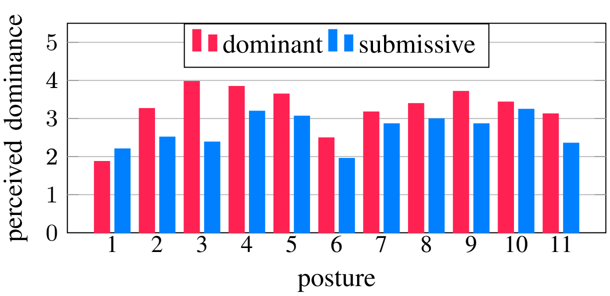
d) Participants: A total of 835 Mechanical Turk workers completed the HIT and were compensated monetarily. Of these, 45 participants failed the trial question and were excluded from further analysis. Another 18 participants were excluded due to low credibility based on a reported age of 1 or 113. The remaining 772 participants were self-identified mostly Americans (n=558) or Indian (n=110), aged between 20 and 83 (Mean=35.42, Std=10.69), and 60% male. Participants where fairly evenly distributed among conditions with a minimum of 89 and maximum of 109 participants per group.

B. Results

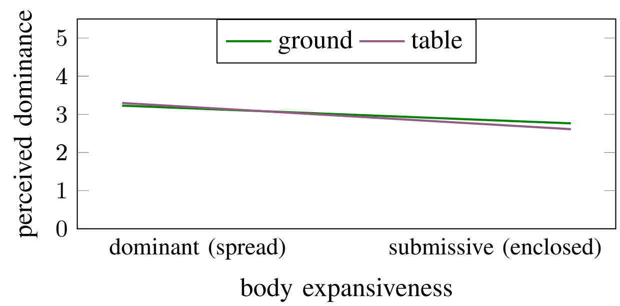
We performed a MANOVA with repeated measures, with within-subject factors the 11 postures, and between-subject factors horizontal view angle, vertical view angle, and body expansiveness.

The tests of between-subject effects showed a significant main effect for body expansiveness on perceived dominance, $F = 262.52, p < 0.001$. This effect was consistent between postures, except for posture 1 (Fig. 2a). Both horizontal and vertical view angle did not significantly affect perceived dominance (respectively $F = 1.56, p = 0.212$, $F = 0.38, p = 0.535$). But, there was a significant, positive, interaction effect for vertical view angle and expansiveness, $F = 9.79, p = 0.002$ (Fig. 2b). In other words, only body expansiveness influenced perceived dominance and did so in the expected direction, this effect was increased when the vertical view angle was decreased (i.e., robot on a table).

The within-subject tests showed a significant main effect of posture on perceived dominance, $F = 182.52, p < 0.001$. Further, there were small though significant interaction effects between posture and each of the factors horizontal angle,



(a) Mean perceived dominance for both submissive and dominant stimuli, given per posture.



(b) Mean perceived dominance for both ground and table placed stimuli, given per body expansiveness condition.

Fig. 2: mean perceived level of dominance expressed by the robot (range 0–5).

vertical angle, and expansiveness. Most prominently posture and expansiveness, $F = 45.23, p < 0.001$.

C. Discussion

First, the effect of manipulation of body expansiveness on perceived dominance shows that expansiveness is an important factor for dominance expression. Although there was an interaction effect with view height this did not hinder perception as intended. Indicating that body expansiveness manipulation can be used to influence perceived dominance, and that this is robust against variations in view angle.

Further, different postures have different associated levels of dominance (Fig. 2a). This is of no surprise given that some postures by nature are more expansive than others. Nonetheless, for all but one postures the body expansiveness manipulation influenced dominance perception in the desired direction. This indicates that body expansiveness modulation can be used to influence perceived dominance independent of specific behaviours.

To summarise, we have identified two methods controlling dominance expression by a robot: posture selection and body expansiveness manipulation. The latter by modulation of the parameters head tilt, arm angle, leg angle, and leg stretch.

V. Study 2: Synthesised Gestures

A. Method

To evaluate the effect of expansiveness modulation applied to motions on observers' perception of the robot's affect expression, we set up an experiment with between-subject variable body expansiveness, and within-subject variable gesture.

a) Stimuli: The proposed modulation can be applied to any robot behaviour. For the purpose of this experiment we selected 10 distinctive behaviours and applied the maximum dominant and submissive modulations. The behaviours were created in Choreograph and designed to express a 'neutral' stance. The resulting submissive, neutral, or dominant versions were shown on a NAO placed in front on a table.

b) Measurement: Perceived dominance was measured on a 9-point Likert scale. We used the Self Assessment Manikin (SAM) [25] because it is a widely acknowledged, validated, instrument measuring affective responses to a wide variety of stimuli. We include all three items (i.e., dominance, valence, arousal) to control for correlations with these factors.

c) Procedure: Participants participated individually and were seated 1.5 meters from the robot. Each participant was assigned to one condition (i.e., neutral, dominant, submissive), and presented the 10 gestures, modulated accordingly, one by one in randomised order. After each gesture the participant completed the SAM questionnaire. Gestures could be viewed repeatedly upon request. A researcher was present in the room to control the robot.

d) Participants: A total of 31 participants were recruited at the University premises, all students or staff. Participants were aged 23–62 (Mean=32.22, std=9.88), mostly male (n=17), and predominantly of Chinese (n=10) or Dutch (n=12) nationality. Eight participants did not provide their age, of these six withheld their nationality, and four their gender as well. Participants were equally balanced between conditions.

B. Results

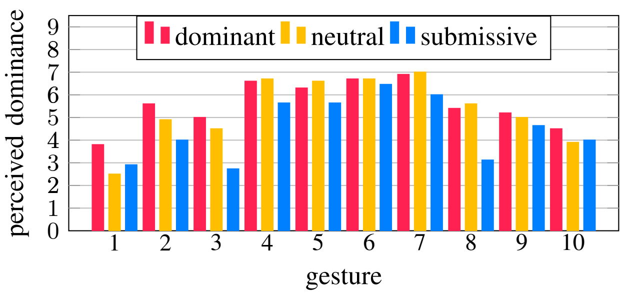
We performed a MANOVA (within-subject factors the 10 gestures and between-subject factor expansiveness) and compared outcomes for perceived dominance, valence and arousal.

Using Pillai's trace, the multivariate test showed a moderate tendency of body expansiveness to affect overall perception, $V = 0.35, F(6, 54) = 1.90, p = 0.098$. No interaction effect between gesture and body expansiveness was found. However, separate univariate ANOVAs on the outcome variables revealed significant positive body expansiveness effects on perceived dominance, $F(2, 28) = 4.41, p = 0.022$; and arousal, $F(2, 28) = 5.10, p = 0.013$. In other words, participants perceived the robot displaying spreading gestures as more dominant ($\mu = 5.6$) and aroused ($\mu = 5.93$) than a robot showing more enclosed gestures (dominance, $\mu = 4.58$; arousal, $\mu = 4.76$), and that these differences were independent of specific gestures.

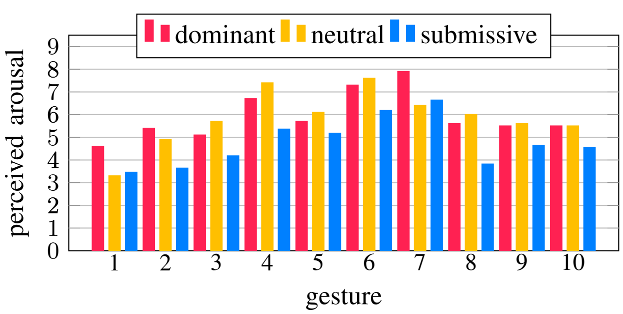
Tests of within-subject effects revealed a small but significant overall effect of gesture on perception, $V = 0.83, F(27, 756) = 10.78, p < 0.001$. Univariate tests on the outcome variables revealed significant effects of gesture for all three factors (dominance, $F = 16.56, p < 0.001$; valence, $F = 13.92, p < 0.001$; arousal, $F = 12.78, p < 0.001$). For none of the factors, an interaction effect between gesture and expansiveness was found. In other words, different gestures elicited different perceptions, but these differences were consistent over body expansiveness conditions (Fig. 3).

C. Discussion

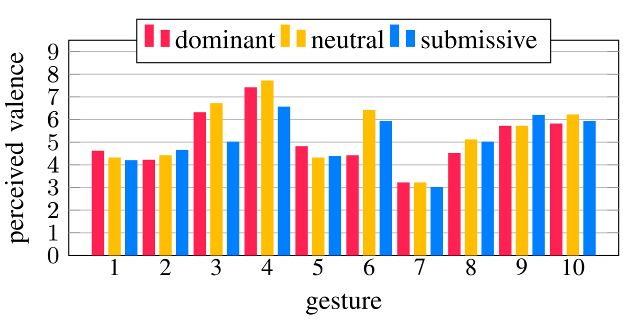
This study shows that, also in motions, body expansiveness influences dominance perception. The effect of body expansiveness is independent of a specific gesture, and correlated with arousal. This might be explained by more dominant behaviours being more expressive, and expressiveness being a factor for arousal display (e.g., [50]). Further, one of the parameters, head tilt, was associated with arousal display (e.g., [40], [51]). Arousal was also found to correlate with valence [15]. However, in our study, body expansiveness did not affect perceived valence (Fig. 3c). This means that body expansiveness could be used to selectively manipulate dominance display without influencing perceived valence (pleasure).



(a) Mean perceived dominance (range 0–9)



(b) Mean perceived arousal (range 0–9)



(c) Mean perceived valence (range 0–9)

Fig. 3: estimated means for user perception of the robot, numbers 1–10 indicate the individual gestures, coloured bars depict the body expansiveness conditions.

As with postures, the body expansiveness effect is consistent over multiple gestures, however, different gestures do convey different levels of dominance. Thus, parameter-based dominance control is limited to relative differences within a behaviour's affective tendency. Considerate behaviour selection is necessary to convey a consistent dominance display over a prolonged interaction sequence. The affective tendencies of behaviours (i.e., postures and gestures) can be used to our advantage. For example, adjusting the frequency of specific gestures to control dominance [46], or selecting types of gestures to express certain roles (e.g., [52], [53]).

We have shown the validity of body expansiveness modulation for dominance expression in both postures and gestures. We show that with a limited set of parameters we can express various degrees of dominance. The joint angles are specific to NAO, but the body expansiveness modulation can be applied to any robot or embodied agent, making the model applicable to other systems and scenario's as well. Further, we discovered distinctive affective patterns in individual gestures. However, extensive evaluation of this effect in interaction is required to support expression of certain roles in interactive scenario's.

VI. Conclusion

In conclusion, we showed that dominance perception of robot gestures and postures can be controlled by behaviour selection and parameter-based body expansiveness manipulation. We found that specific postures and gestures have a natural tendency towards being perceived as more or less dominant. Further, the manipulation effect was consistent for a variety of behaviours except a sitting pose. A clear view on the robot may increase the effect. Manipulation was based on inter-human interaction cues for dominance display: vertical head angle, horizontal shoulder angle, horizontal and sagittal hip angle, and vertical leg stretch. Our results are limited by the number of behaviours evaluated and application on a NAO robot and should be replicated with other robot types.

References

[1] Albert Mehrabian. Nonverbal communication. In *symp. on motivation*, pages 107–161, Nebraska, 1971. University of Nebraska Press.

[2] Gordon B Moskowitz. *Social cognition: Understanding self and others*. Guilford Press, New York, 2005.

[3] Terrence Fong, Illah Nourbakhsh, and Kerstin Dautenhahn. A survey of socially interactive robots. *Robot. and autonomous syst.*, 42(3-4):143–166, 2003.

[4] A. Vinciarelli, M. Pantic, D. Heylen, C. Pelachaud, I. Poggi, F. D'Errico, and M. Schroeder. Bridging the Gap Between Social Animal and Unsocial Machine: A Survey of Social Signal Processing. *Affect. Comput.*, 3(1):69–87, 2011.

[5] Ginevra Castellano, Maurizio Mancini, Christopher Peters, and Peter W McOwan. Expressive copying behavior for social agents: A perceptual analysis. *Trans. on Syst., Man, and Cybern.*, 42(3):776–783, 2012.

[6] Céline Clavel, Justine Plessier, Jean-Claude Martin, Laurent Ach, and Benoit Morel. Combining facial and postural expressions of emotions in a virtual character. In *Int. Workshop on Intell. Virtual Agents*, pages 287–300. Springer, 2009.

[7] Matthieu Destephe, Andreas Henning, Massimiliano Zecca, Kenji Hashimoto, and Atsuo Takanishi. Perception of emotion and emotional intensity in humanoid robots gait. In *Proc. 2013 Int. Conf. on Robot. and Biomimetics*, pages 1276–1281. IEEE, 2013.

[8] Daisy N Kurien. Body language: Silent communicator at the workplace. 2010.

[9] Iris Cohen, Rosemarijn Looije, and Mark A Neerincx. Childs perception of robots emotions: effects of platform, context and experience. *Int. J. of Social Robot.*, 6(4):507–518, 2014.

[10] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. Mood expression through parameterized functional behavior of robots. In *Proc. Int. Symp. on Robot and Human Interactive Commun.*, pages 533–540, Gyeongiu, Korea, 2013. IEEE.

[11] Yueh-Hung Lin, Chia-Yang Liu, Hung-Wei Lee, Shwu-Lih Huang, and Tsai-Yen Li. Evaluating emotive character animations created with procedural animation. In *Int. Workshop on Intell. Virtual Agents*, pages 308–315, Amsterdam, The Netherlands, 2009. Springer.

[12] Aryel Beck, Antoine Hiolle, Alexandre Mazel, and Lola Cañamero. Interpretation of emotional body language displayed by robots. In *3rd Int. Workshop on Affect. interaction in natural environments*, pages 37–42, 2010.

[13] James A Russell. A circumplex model of affect. *J. of personality and social psychology*, 39(6):1161, 1980.

[14] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. The relative importance and interrelations between behavior parameters for robots' mood expression. In *Proc. Conf. on Affect. Comput. and Intell. Interaction*, pages 558–563. IEEE, 2013.

[15] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark Neerincx. Bodily mood expression: Recognize moods from functional behaviors of humanoid robots. In *Proc. Int. Conf. on social robot.*, pages 511–520, Bristol, UK, 2013. Springer.

[16] Susan T Fiske, Amy JC Cuddy, and Peter Glick. Universal dimensions of social cognition: Warmth and competence. *Trends in cogn. sci.*, 11(2):77–83, 2007.

[17] Steve L Ellyson and John F Dovidio. Power, dominance, and nonverbal behavior: Basic concepts and issues. In *Power, dominance, and nonverbal behavior*, pages 1–27. Springer, 1985.

[18] Paul Ekman. Emotional and conversational nonverbal signals. In *Language, knowledge, and representation*, pages 39–50. Springer, 2004.

[19] Definition of dominance in English. https://en.oxforddictionaries.com/definition/dominance. Accessed: 2019-02-19.

[20] Jerry S Wiggins. An informal history of the interpersonal circumplex tradition. *J. of personality assessment*, 66(2):217–233, 1996.

[21] Timothy Leary. Interpersonal diagnosis of personality. *Amer. J. of Physical Med. & Rehabilitation*, 37(6):331, 1958.

[22] Sebo Onno Ebbens and Simon Ettekoven. *Effectief leren: basisboek*. Noordhoff Uitgevers, 2016.

[23] Adri Amelsvoort, Imke Rispens, and Henny Grolman. *Handleiding verhoor*. Stapel & De Koning, 2010.

[24] M. Schmid Mast and J. A. Hall. *Social signal processing*, chapter The vertical dimension of social signaling, pages 34–45. Cambridge University Press, Cambridge, 2017.

[25] Margaret M Bradley and Peter J Lang. Measuring emotion: the self-assessment manikin and the semantic differential. *J. of behavior therapy and experimental psychiatry*, 25(1):49–59, 1994.

[26] James A Russell and Albert Mehrabian. Evidence for a three-factor theory of emotions. *J. of res. in Personality*, 11(3):273–294, 1977.

[27] Daniel Schacter, Daniel Gilbert, Daniel Wegner, and Bruce M Hood. *Psychology: European Edition*. Macmillan Int. Higher Education, 2011.

[28] Dana R Carney, Judith A Hall, and Lavonia Smith LeBeau. Beliefs about the nonverbal expression of social power. *J. of Nonverbal Behavior*, 29(2):105–123, 2005.

[29] Judith A Hall, Erik J Coats, and Lavonia Smith LeBeau. Nonverbal behavior and the vertical dimension of social relations: a meta-analysis. *Psychological bulletin*, 131(6):898, 2005.

[30] Dana R Carney, Amy JC Cuddy, and Andy J Yap. Power posing: Brief nonverbal displays affect neuroendocrine levels and risk tolerance. *Psychological sci.*, 21(10):1363–1368, 2010.

[31] Amy JC Cuddy, Caroline A Wilmuth, Andy J Yap, and Dana R Carney. Preparatory power posing affects nonverbal presence and job interview performance. *J. of Appl. Psychology*, 100(4):1286, 2015.

[32] Olga Bialobrzeska and Michal Parzuchowski. Size or openness: expansive but closed body posture increases submissive behavior. *Polish Psychological Bulletin*, 47(2):186–194, 2016.

[33] Michael Kipp and Jean-Claude Martin. Gesture and emotion: Can basic gestural form features discriminate emotions? In *Int. Conf. on affect. comput. and intell. interaction*, pages 1–8, Amsterdam, Netherlands, 2009. IEEE.

[34] Michael Argyle. *Bodily communication*. Routledge, 2013.

[35] 13 revealing body language hand gestures. https://nicolasfradet.com/hand-body-language. Accessed: 2017-01-17.

[36] 20 hand gestures you should be using. http://www.scienceofpeople.com/2015/08/how-to-speak-with-your-hands/. Accessed: 2017-01-17.

[37] Thomas Leonard and Fred Cummins. The temporal relation between beat gestures and speech. *Language and Cogn. Processes*, 26(10):1457–1471, 2011.

[38] Alain Mignault and Avi Chaudhuri. The many faces of a neutral face: Head tilt and perception of dominance and emotion. *J. of nonverbal behavior*, 27(2):111–132, 2003.

[39] Nicholas O Rule, Reginald B Adams Jr, Nalini Ambady, and Jonathan B Freeman. Perceptions of dominance following glimpses of faces and bodies. *Perception*, 41(6):687–706, 2012.

[40] Aryel Beck, Lola Cañamero, and Kim A Bard. Towards an affect space for robots to display emotional body language. In *Proc. 19th Int. symp. in robot and human interactive commun.*, pages 464–469, Viareggio, Italy, 2010. IEEE.

[41] Cynthia Breazeal. Emotion and sociable humanoid robots. *Int. j. of human-comput. stud.*, 59(1-2):119–155, 2003.

[42] Mathieu Chollet, Magalie Ochs, and Catherine Pelachaud. From non-verbal signals sequences mining to bayesian networks for interpersonal attitude expression. In *Proc. Int. Conf. on Intell. Virtual Agents*, volume 2792, pages 120–133, Boston, United States, 2014. Springer.

[43] Brent Lance and Stacy C Marsella. Emotionally expressive head and body movement during gaze shifts. In *Proc. Int. Conf. on Intell. Virtual Agents*, volume 2792, pages 72–85. Springer, 2007.

[44] Brian Ravenet, Magalie Ochs, and Catherine Pelachaud. From a user-created corpus of virtual agent's non-verbal behavior to a computational model of interpersonal attitudes. In *Proc. Int. Conf. on Intell. Virtual Agents*, volume 8108 LNAI, pages 263–274. Springer, 2013.

[45] Gabriel Castillo and Michael Neff. *What do we express without knowing? Emotion in Gesture*, pages 702–710. 2019.

[46] Wafa Johal, Sylvie Pesty, and Gaelle Calvary. Towards companion robots behaving with style. In *Proc. 23rd Int. Symp. on Robot and Human Interactive Commun.*, pages 1063–1068, Edinburgh, Scotland, 2014. IEEE.

[47] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. Effects of bodily mood expression of a robotic teacher on students. In *Proc. Int. Conf. on Intell. Robots and Syst.*, pages 2614–2620, Chicago, Illinois, 2014. IEEE.

[48] Jaewook Kim, Sonya S Kwak, and Myungsuk Kim. Entertainment robot personality design based on basic factors of motions: A case study with rolly. In *Proc. Int. Symp. on Robot and Human Interactive Commun.*, pages 803–808, Toyama, Japan, 2009. IEEE.

[49] Martin Saerbeck and Christoph Bartneck. Perception of affect elicited by robot motion. In *Proc. Int. Conf. on Human-robot interaction*, pages 53–60, Osaka, Japan, 2010. IEEE.

[50] Nele Dael, Martijn Goudbeek, and Klaus R Scherer. Perceived gesture dynamics in nonverbal expression of emotion. *Perception*, 42(6):642–657, 2013.

[51] Martin Inderbitzin, Aleksander Väljamäe, Jose Maria Blanco Calvo, Paul FMJ Verschure, and Ulysses Bernardet. Expression of emotional states during locomotion based on canonical parameters. In *Proc. 9th Conf. on Automatic Face and Gesture Recognition*, pages 809–814, Santa Barbara, CA, 2011. IEEE.

[52] Amy L Baylor and Yanghee Kim. Simulating instructional roles through pedagogical agents. *Int. J. of Artificial Intell. in Edu.*, 15(2):95–115, 2005.

[53] Truong-Huy D Nguyen, Elin Carstensdottir, Nhi Ngo, Magy Seif El-Nasr, Matt Gray, Derek Isaacowitz, and David Desteno. Modeling warmth and competence in virtual characters. In *Proc. Int. Conf. on Intell. Virtual Agents*, pages 167–180, Delft, The Netherlands, 2015. Springer.