--- Final Draft Version, accepted by ACII 2013 ---

The Relative Importance and Interrelations between Behavior Parameters for Robots' Mood Expression

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***Abstract*—Bodily expression of affect is crucial to human robot interaction. Our work aims at designing bodily expression of mood that does not interrupt ongoing functional behaviors. We propose a behavior model containing specific (pose and motion) parameters that characterize the behavior. Parameter modulation provides behavior variations through which affective behavioral cues can be integrated into behaviors. To investigate our model and parameter set, we applied our model to two concrete behaviors (waving and pointing) on a NAO robot, and conducted a user study in which participants (N=24) were asked to design such variations corresponding with positive, neutral, and negative moods. Preliminary results indicated that most parameters varied significantly with the mood variable. The results also suggest that the relative importance may be different between parameters, and parameters are probably interrelated. This paper presents the analysis of these aspects. The results show that the spatial extent parameters (hand-height and amplitude), the head vertical position, and the temporal parameter (motion-speed) are the most important parameters. Moreover, multiple parameters were found to be interrelated. These parameters should be modulated in combination to provide particular affective cues. These results suggest that a designer should focus on the design of the important behavior parameters and utilize the parameter combinations when designing mood expression.**

Keywords—nonverbal cues; bodily expression; affect; mood; behavior model; parameterization; social robots; HRI;

I. INTRODUCTION

Bodily expression of affect is a key ability of social robots [1]. It is crucial to human robot interaction (HRI) because it helps humans to perceive the internal states (e.g., beliefs, intentions, and emotions) of robots, and it improves the naturalness of HRI and the life-like quality of robots [2]. Bodily expression is also important for robots that lack sophisticated facial features such as NAO, QRIO and ASIMO. Current bodily expression of affect usually consists of body actions that express emotions deliberately. For example, raising both hands shows happiness [3]; arms akimbo shows anger [4]; covering eyes by hands shows fear [5]. However, these body actions rise and dissipate quickly and do not extend over time. Moreover, these body actions may interrupt functional behaviors during a task; functional behaviors also hinder such actions from expressing a long-term affect like mood. For example, a robot cannot express an excitement mood by raising both hands repeatedly while the robot is pointing to the object that makes it excited for long. Parkinson proposed that moods may be expressed via bodily postures [6]. Breazeal et al. [7] defined implicit communication (i.e., robots do not communicate deliberately), which conveys robots' internal states via behavioral cues. Inspired by them, we believe that mood can be expressed implicitly through affective behavioral cues. Our work aims at integrating bodily expression of mood with task-related behaviors, by embedding affective behavioral cues into these functional behaviors. As a result, robots can convey affects continuously over time, even during a task execution. Therefore, our proposed bodily mood expression may enhance the effect of the affective expression on HRI.

We propose a layered behavior model that generates behavior variations through behavior parameter modulation, and the variations provide affective cues. The model contains parameters (e.g., speed, amplitude, and repetition) that are applicable to a broad range of behaviors. In our model, moods do not trigger behaviors but influence the behavior appearance. As a result, mood expression does not interrupt task scheduling. In previous work [8], we applied this model to two concrete behaviors of the NAO robot, and studied the relation between mood variables and behavior parameter modulation and obtained general design principles for each parameter. This paper addresses the relative importance and the interrelations between parameters. The results provide insights into behavior parameter modulation for expressing moods, and provide criteria for simplifying the behavior generation system of a robot. Designers may focus more on the highly important parameters when designing bodily expression of mood. The parameter space of bodily expressions can be less complex by removing the less important parameters. Moreover, we also found that multiple parameters have to be modulated in concert to express a particular mood, and some of them vary correlatively. In this case, less parameter modulation principles are needed when one function is built to map mood variables to interrelated parameters as a whole.

The remainder of the paper is organized as follows. Section II introduces the research on parameterized behavior models. Section III describes our behavior model and the implementation into concrete behaviors; Section IV describes the experiment and the initial findings. Section V reports our findings about the relative importance and interrelations between behavior parameters; Section VI concludes the main findings of this study and proposes the future work.

II. Related Work

One way of generating affective behavioral cues is to modulate behavior parameters. In this way, affect can be reflected by the same behavior executed in different "styles", rather than the behavior "contents" per se. Laban movement analysis (LMA) [9] is composed of a broad range of parameters that models body movements from different aspects, e.g., effort and shape. It has been used in expressive gesture synthesis for virtual agents (e.g., EMOTE [10]) and emotion expression for robots (e.g., [11]). Unlike EMOTE, which performs as a post-process of generated behaviors, we define interfaces (i.e., behavior parameters) simultaneously we create the functional profile of the behavior, so that mood expression (by modulating these parameters) can exist in concord with behavior functions. Wallbott [12] studied humans' bodily movements that express emotions. The behavior pattern is annotated as movement "quality" defined by three dimensions. Pelachaud et al. [13] characterized the expressivity of nonverbal behavior (i.e., how a behavior is executed) using six parameters: spatial, temporal, fluidity, power, overall activation, and repetition. They were applied to an embodied conversational agent Greta, so that Greta can communicate her cognitive and affective states through modulated gestures. The parameters in the above studies are abstract and have to be transformed into concrete ones while applying them to a particular behavior. Several concrete parameters can represent the same abstract one. For example, the spatial extent [13] can present horizontal extent (amplitude or wideness), vertical extent (height), or radial extent (e.g., the outstretching extent of an arm). The speed parameter can present the speeds of different phases of a behavior (e.g., motion speed and decay speed). These different transformed parameters may produce different affective cues. Moreover, when applying these parameters to a functional behavior of a particular robot, some of them may be restricted by the behavior function and the physical constraints of the robot. We study behavior parameter modulation for mood expression with the parameters that exist inherently in the behavior and can be modulated without interfering with behavior functions.

The robotic behaviors which parameter modulation has been applied to usually involved merely a few degrees of freedom (DOFs) [11, 14]. Whether parameter modulation of a high-DOF behavior is effective for mood expression remains a question, especially in the presence of the behavior function. In addition, the underlying control mechanism of high-DOF behaviors can be more complex. It may be difficult to apply a complex parameter modulation model to those behaviors. Parameter modulation can be simplified by selecting a sufficient set of parameters that can express moods efficiently. Criteria are needed for selecting a minimum set. Yet, the priorities of parameters are not clear. Moreover, modulating a single parameter may be insufficient for expressing a particular mood. Crane et al. showed that some parameters need to be modulated in combination for expressing a particular affect [16]. Yamaguchi et al. [14] proposed a model in which four emotions can be expressed through modifying amplitude, speed, and position. They applied the model into single-arm behaviors of an AIBO robot. They also found certain emotions could not be expressed only by a single parameter. For example, fast motion can be applied to both joy and anger. Thus, other parameters have to be applied together. For high-DOF behaviors, interrelations between parameters also become more complex. It is necessary to clarify the interrelations between parameters to find such combinations for expressing affect more efficiently. We studied high-DOF functional behaviors and investigated these issues by an experiment in which participants were involved in designing mood expression through parameter modulation.

Layered models (e.g., [14] [15]) were developed to link the affect of robots or virtual agents to behavior parameters. Our model adopts the layered architecture. Unused body parts can also vary behavior styles without interrupting task execution. Brooks and Arkin [17] proposed a behavioral overlays model that alters the overall appearance of robots' functional behaviors by overlaying behaviors of unused body resources. Beck et al. [18] report that head movements have a strong effect on expressing affect. Therefore, we added head into functional behaviors with two pose parameters, head-up-down, and head-left-right.

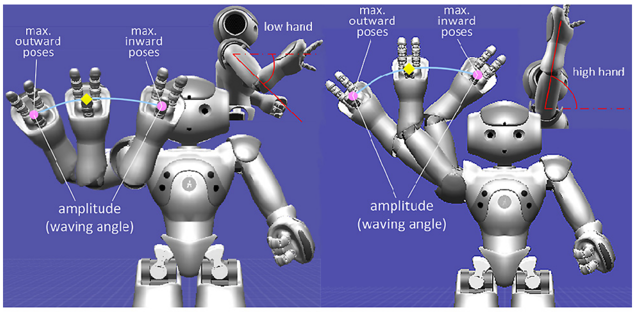
III. Behavior Model and Implementations

A. General Behavior Model

The parameterized behavior model (Fig.2, Fig.4) consists of three layers: 1) a drive layer; 2) a behavior parameterization layer; and 3) a joint configuration layer. The drive layer contains the task scheduler and the affect generator. We modeled mood using dimensional variables in the affect generator. The task scheduler decides the current behavior to be performed according to behaviors' functional profiles. Each behavior has its own functional profile that constrains the joints, while affect determines the behavior parameters which change the joints within functional bounds, generating behavior variations. Thus, from the top layer, the task scheduler and affect generator can work simultaneously and separately without interfering with each other. In the behavior parameter layer, pose and motion parameters serve as interfaces for the drive layer to stylize the behavior. Pose parameters control the key postures (position, shape, and direction) of effectors (a chain of joints, e.g., arm, leg, and neck), while movements are generated by these key postures and interpolation. Motion parameters depict the dynamics of a motion including velocity, continuity, and repetition. We constructed the behavior profiles by mimicking humans' behaviors and according to social conventions (i.e., people understand the behaviors with common sense). The parameters were defined during the construction of behaviors' functional profiles so that balance of behavior variations and the maintenance of the behavior function can be better achieved.

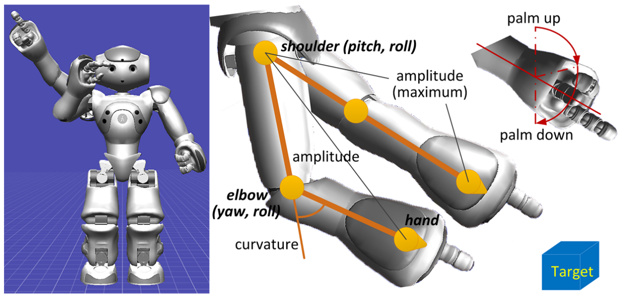
B. Implementation

The behavior model was applied to a greeting gesture, waving (Fig.1) and a deictic gesture, pointing (Fig.3) of a NAO robot (academic version 3.3). For each behavior we used three pose parameters for the right arm and four motion parameters. Six DOFs (degrees of freedom) exist in the arm including Shoulder (Pitch, Roll), Elbow (Yaw, Roll), WristYaw, and Fingers, and two DOFs including Head (Pitch, Yaw) in the neck. Although NAO emulates the human body, differences



(a) waving mode 1 (b) waving mode 2

Fig. 1. The pose parameters of waving behavior



(a) preparation and pointing poses (b) pose parameters

Fig. 3. The pose parameters of pointing behavior

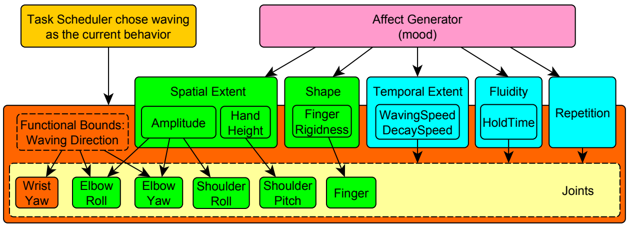


Fig. 2. The parameterization of waving behavior

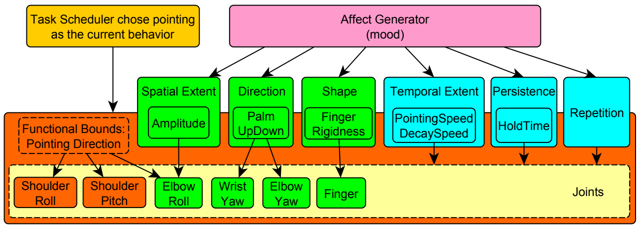


Fig. 4. The parameterization of pointing behavior

remain in the arm. The wrist-pitch is missing, and the angle range of shoulder-roll and elbow-roll is limited.

We define waving as one hand swinging between two horizontally aligned positions repeatedly, and the palm should always face forward. Pose parameters determine the maximum inward and outward poses (Fig.1). The pose parameters of waving are hand-height, finger-rigidness, and amplitude. Hand-height determines the vertical position of the poses, while amplitude determines the horizontal. Fig.1 shows low and high hand positions. In our design, waving has two modes, which are switched according to the hand-height. Waving can be generated by controlling ElbowYaw and ShoulderRoll joints when the hand-height is low (Fig.1a), and by controlling ElbowRoll and ShoulderRoll joints when the hand-height is high (Fig.1b). The amplitude is the waving angle. Finger-rigidness controls the straightness of NAO's fingers. Other joints (WristYaw and ElbowRoll when the hand-height is low; WristYaw and ElbowYaw when the hand-height is high) are constrained to keep the palm facing forward.

We define pointing behavior as the arm stretching out from the preparation pose to the pointing pose (Fig.3a), with which the index finger aims at a specified target (Fig.3b). Since NAO's three fingers cannot be controlled separately, two of them were stuck to the hand allowing only one finger to move as index finger. The pose parameters of pointing are palm-direction, finger-rigidness, and amplitude (Fig.3b). Palm-direction controls the facing direction of the palm for the pointing pose (shown in the top-right figure of Fig.3b). Amplitude determines the outstretching extent of the arm for the pointing pose. Finger-rigidness controls the straightness of the index finger, which is constrained as the pointing finger cannot be fully bent in the pointing pose.

Four motion parameters were adapted from [13] and [19]: 1) Motion-speed (temporal extent) refers to the velocity of the arm swings for waving (waving-speed), or the arm outstretching from preparation pose to the pointing pose for pointing (pointing-speed). 2) Decay-speed (temporal extent) refers to the velocity of the arm returning to initial pose. 3) Repetition is the number of swings for waving, and the number of outstretching actions for pointing. 4) Hold-time (fluidity) determines duration of the arm waiting at the endpoints of a swing for waving, or at the pointing pose for pointing. For the head, we used the same values for motion parameters as used for the arm movement except for the repetition (the head never repeats). Thus, each behavior has nine parameters in total.

IV. EXPERIMENT AND INITIAL FINDINGS

To study the parameterized behavior model, we conducted an experiment in which participants were asked to design mood expression by adjusting the nine parameters for each of the two behaviors corresponding to different moods characterized by valence. Although valence is a dimensional scale, five different levels were used for the experiment. We used very-unhappy, unhappy, neutral, happy, and very-happy to describe to ensure that participants can understand them. We did not constrain the context of arousal. Participants can display adjusted behaviors on a real NAO robot, so that they can test resulting behaviors. They were also asked to provide their design rationale. In this way, participants provided various self-evaluated parameter settings to us, and we extracted design principles from their settings and comments. 24 university students (14 males, 10 females) with an average age of 23 (SD=4) participated in this experiment. More details can be found in [8].

We have analyzed the participants-created settings using repeated-measures ANOVA, and obtained the relation between valence and behavior parameters [8], which we summarize as follows. Results showed that almost all parameters of both behaviors varied significantly with valence. This indicates that our model and behavior parameter set are promising for

TABLE I. PARAMETERS THAT VARY SIGNIFICANTLY WITH MOOD

Waving				Pointing			
Parameters	***Trend†***	***Sig.‡***	η^2	***Parameters***	***Trend†***	***Sig.‡***	η^2
HandHeight	+	***	0.955	**HeadVer.**	+	***	0.895
HeadVer.	+	***	0.938	**PntSpd**	+	***	0.882
WavSpd	+	***	0.894	**Amplitude**	+	***	0.818
Repetition	+	***	0.815	**Repetition**		***	0.732
FingerRig.	+	***	0.781	**DecaySpd**	+	**	0.578
DecaySpd	+	***	0.770	**HoldTime**		*	0.414
Amplitude	+	**	0.515	**PalmDir**	+	*	0.402
HoldTime			0.348	**FingerRig.**			0.265
HeadHor.			0.217	**HeadHor.**			0.123

†These parameters increase with increasingly positive valence.
‡ p<0.05, ** p<0.01, *** p<0.001*

generating behavioral cures for mood expression. Moreover, the results of pairwise *t* tests suggest that most parameters are positively correlated with valence (Table I). Since these parameters follow the same trend, we speculate that some parameters are probably interrelated, and they should probably be modulated in combination when expressing a particular mood. The interrelations can also simplify the mapping from mood variables to behavior parameters. Moreover, the effect sizes η^2 of ANOVAs indicated that the strength of the association between valence and each behavior parameter may be different. Therefore, we speculate that the importance of each parameter is different. Parameters in Table I are sorted by the effect size η^2. In this paper, we looked at the parameters with large (>0.5) effect size, and the relative importance is further assessed by analyzing the parameter settings and the empirical data provided by participants. The importance provides a benchmark for simplifying the behavior model by removing the less important parameters.

V. RELATIVE IMPORTANCE AND INTERRELATIONS

A. Data Reliability

Questions (using 5-point Likert scale) about participants' confidence of their designs (mean=3.85, SD=0.58), whether the moods can be recognized (mean=4.08, SD=0.58), and task complexity (mean=3.33, SD=0.87) suggested that participants were successful at the task. Before the main analysis, Cronbach's α was used to test whether the values for each parameter of five mood levels are consistent across 24 participants. The data reliability indicates the validity of the results of the main analysis. Based on the reliability, we can select parameters for the main analysis. Results show that the data of the head-left-right of both behaviors are unreliable (below 0.60). The data of all other parameters are reliable: for waving the α values from 0.833 to 0.994; for pointing the α values range from 0.729 to 0.990. Therefore, all parameters except the head-left-right were selected for the main analysis.

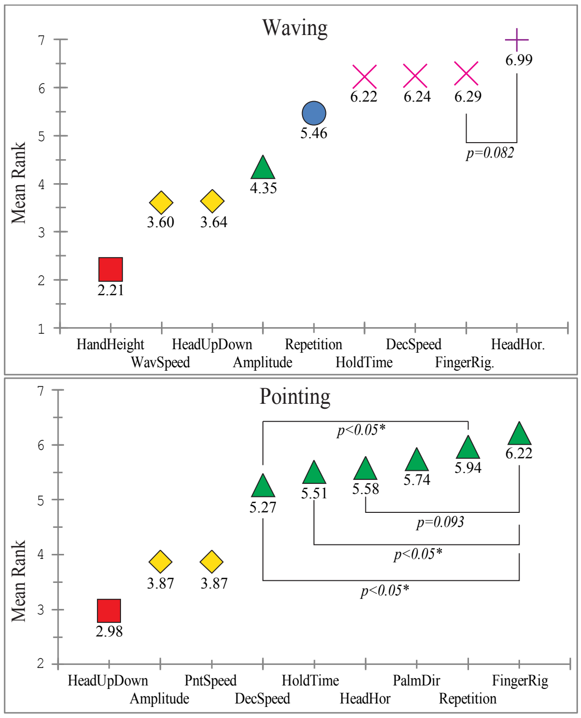


Fig. 5. The results of Friedman test and Wilcoxon tests for the two behaviors across all mood levels; the mean ranks are denoted under each symbol; the significances are uncorrected

B. The Relative Importance of Parameters

The relative importance of parameters was assessed through the user settings (objective data) and the user ranks (empirical data) of parameters. Multivariate linear regression was used to analyze the relationship between the mood variable (outcome variable) and each behavior parameter (predictor variables). The standardized coefficient β and ΔR^2 of each predictor indicates its contribution to the outcome variable, i.e., its importance in the model. Among the parameters that have high reliability, the behavior parameters that vary significantly with mood (see Section IV) were selected as predictors. The important parameters were selected using backward-stepwise method (to reduce Type II error). Afterwards, we entered these parameters hierarchically (blockwise entry) to obtain a forward change statistics. Table II shows the minimum set of parameters for waving and pointing behaviors in order of importance suggested by the multivariate regression results.

TABLE II. IMPORTANCE SUGGESTED BY MULTIVARIATE REGRESSION

Waving	***Coefficients***		***Change Statistics***				
Parameters	β	***Sig.***	*step*	R^2	ΔR^2	ΔF	***Sig.***
HeadVer.	0.483	0.000	1	0.842	0.842	627.436	0.000
HandHeight	0.236	0.000	2	0.886	0.044	44.953	0.000
WavingSpd	0.212	0.000	3	0.907	0.021	25.436	0.000
Repetition	0.071	0.077	4	0.910	0.003	3.723	0.056
Amplitude	0.065	0.054	5	0.913	0.003	3.790	0.054
Pointing	***Coefficients***		***Change Statistics***				
Parameters	β	***Sig.***	*step*	R^2	ΔR^2	ΔF	***Sig.***
HeadVer.	0.727	0.000	1	0.767	0.767	389.083	0.000
Amplitude	0.149	0.007	2	0.783	0.016	8.879	0.004
PointingSpd	0.094	0.085	3	0.788	0.005	3.014	0.085

Each parameter was entered for each step, and the coefficients of the final step are shown.

Friedman test with Kendall's *W* was used to analyze the user ranks of parameters. The analysis was performed across all mood levels to assess the relative importance of each parameter, and performed for each mood level separately to test how the importance of each parameter varied with mood levels. Kendall's *W* was used to assess the consistency of participants' ranks. The results show that the importance of waving parameters is different ($\chi^2(8) = 334.211$, $p<0.001$, $W = 0.348$), and the importance of pointing parameters is also different ($\chi^2(8) = 164.327$, $p<0.001$, $W = 0.171$). Fig.5 shows the mean rank of each parameter. Parameters with high

TABLE III. THE MODULATION OF PARAMETERS IN COMBINATION

Waving							
Expressed Mood		*Parameter Modulation*					*Freq.*
Negative	**angry**	MS+	DS+	AMP-			2
	bored	MS-		AMP+			5
	sad	MS-	DS-	AMP-	HT-		7
	depressed	MS-	DS-	AMP-	HT+		8
Positive	**excited**	MS+	AMP-	HH+	HT-		6
	happy	MS+	AMP+		HT-		12
	elated	MS++	AMP+	REP+	HT-		5
Pointing							
Expressed Mood		*Parameter Modulation*					*Freq.*
Negative	**mad/aggressive**	MS++	DS++		REP+		3
	angry	MS+	DS+				5
	sad	MS-	DS-				12
Positive	**elated**	MS+	AMP+	HT-	REP++		5
	happy	MS+	AMP+		REP+		14
	pleased	MS+	AMP+		REP=0		2

MS: motion-speed, DS: decay-speed, AMP: amplitude, HT: hold-time, REP: repetition, HH: hand-height. The +/- symbols mean increase/decrease from the neutral values. The ++ means great increase, and it is differentiated from + based on clustering.

TABLE IV. REGRESSIONS BETWEEN PARAMETER INCREMENTS

Waving	*X*	*Y*	*Model*	R^2
Negative	ΔWavingSpeed	ΔDecaySpeed	y=0.663x-0.003	0.409
	ΔDecaySpeed	ΔFingerRigidness	y=1.568x-0.144	0.385
Positive	ΔWavingSpeed	ΔDecaySpeed	y=0.779x-0.010	0.390
Pointing	*X*	*Y*	*Model*	R^2
Negative	ΔPointingSpeed	ΔRepetition	y=4.961x+0.614	0.497
		ΔDecaySpeed	y=0.624x-0.020	0.383
		ΔFingerRigidness	y=0.734x-0.028	0.424
		ΔHeadUpDown	y=8.272x-4.013	0.317
Positive	ΔPointingSpeed	ΔRepetition	y=14.229x-0.341	0.423
	ΔRepetition	ΔHoldTime	y=-0.522x+0.475	0.462

The symbol Δ means the increment from the neutral value.

importance (low mean rank) are sorted to the left of the horizontal axis. Then we used Wilcoxon tests to compare the importance of parameters in pairs. Parameters are grouped according to their importance; different groups are marked with different symbols and colors (Fig.5). Significance was found between each pair of the parameters from different groups, except for the annotated one. Therefore, we obtained the relative importance of each group. The results of analyzing the parameter settings and the empirical ranks are overall consistent. Combining these results, we conclude that the minimum parameter set of waving is 1) hand-height, 2) waving-speed, 3) head-up-down, 4) amplitude, and 5) repetition, and the minimum set of pointing is 1) head-up-down, 2) amplitude, and 3) pointing-speed. Moreover, the head-up-down, motion-speed, and amplitude were ranked most important for *both* behaviors. Thus, these parameters are probably also important for other behaviors.

Friedman tests were also carried out for each mood level separately to test how the importance of each parameter varied with mood levels. Results show that the mean ranks of each parameter in different mood conditions are consistent with the overall result, although they vary slightly with moods. Among the five important parameters of waving, across all mood levels the hand-height is top ranked, followed by waving-speed, then amplitude, and then repetition; The head-up-down was top ranked for negative moods, while it dropped to the middle for positive and neutral moods. This suggests that a lowered head is important for showing negative moods, while a raised head is relatively less important for showing positive moods. However, among the three important parameters of pointing, the head-up-down was top ranked for all moods except neutral, followed by the pointing-speed and amplitude. It seems more difficult to express moods by arm movement for pointing than waving, since the head-up-down played a more important role in expressing positive moods for pointing.

C. Interrelations between Parameters

This section focuses on the interrelations between behavior parameters. From the design rationale provided by participants, we found that participants considered several parameters in combination when they were designing a particular expression. To clarify how general these patterns were among participants, we categorized participants' parameters settings using hiearchical clustering analysis with behavior parameters as predictors, and labelled the parameter modulation patterns of these combinations according to their design rationale. Table III show these combinations and their occurrence. The mood levels we chose for this test are 1) very-unhappy (negative condition), and 2) very-happy (positive condition), because the change of each parameter is larger in these extreme conditions and thus less susceptible to the individual differences. To minimize the random effect caused by individual differences on the neutral point, we subtracted the parameter value of each sample (N=24) of very-unhappy and very-happy from its corresponding neutral value.

We inteprete these patterns in light of participants' rationale as follows. For the waving of a negative mood, the majority of participants combined slow waving-speed and decay-speed with small amplitude making the movement small and less energetic to show sadness. With this settings, some participants increased the hold-time to make the movement sluggish and even slower overall. This combination expresses a mood of depression. Some participants combined large amplitude and slow waving-speed to express boredom. When speed is slow, large amplitude made the speed of the overall movement even slower. Similarly, small amplitude made the speed of the overall movement rapid when the speed parameters were set fast. Two participants combined fast waving-speed and decay-speed with a small amplitude to express anger. For the waving of a positive mood, the majority combined fast waving-speed with large amplitude to show happiness, while five participants further increase the waving-speed and combined more repetition and short hold-time to express elation. Six participants combined fast waving-speed but small amplitude to create a feeling of rapidness for expressing excitement. Here, the hand-height was set high to present a postive feeling, otherwise the rapidness may be confused with a negative mood. Thus, the amplitude played different roles in mood expression when combined with different speed conditions. In addition, waving-speed correlates with decay-speed for both negative and positive conditions (Table IV). Participants also mentioned that these two speeds are related and fast waving-speed combined with fast decay-speed gave an "aggressive" feeling to express a negative mood. Besides, almost all participants set waving-speed faster than decay-speed across all mood levels. The finger-rigidness was also found to correlate with both speeds (Table IV). Bent fingers usually express a fatigue (low energy) feeling, while straight fingers accord better with fast speed showing high energy.

For the pointing of a negative mood, half the participants combined slow pointing-speed and slow decay-speed to express sadness. Five participants combined fast pointing-speed and fast decay-speed to show anger. Some of them also decreased the hold-time, because short hold-time caused the pointing pose to decay immediately showing impatience, which enhanced the anger expression. Three participants further increased waving-speed and decay-speed and combined with more repetition to show "madness" or "aggressive". In addtion, the decay-speed positively correlates with the pointing-speed (Table IV). The head-up-down positively correlates to the repetition and two speed parameters, since a lowered head accords with a "sad" mood but not an "angry" mood. The finger was also found to correlate positively with these parameters for matching the energy level. For the pointing of a positive mood, the most frequent combination used by participants is fast poingting-speed and large amplitude, which shows pleasure. When they are combined with a moderate repetition (1 to 3), the pointing looks happier. When they are combined with a high repetition (4 to 5), the pointing shows elation. Besides, the hold-time was found negatively correlated with the repetition (Table IV). Participants explained that both repeated pointing and long-hold pointing pose could show emphasis on the target. Using both cues is unnecessary. The pointing-speed positively correlates with the repetition because fast speed accords better with repeated motion.

In sum, the same parameter may function differently for expressing moods when other parameters have changed. These findings provide a general principle for designing bodily expression of mood using parameter modulation: it is more important to modulate a combination of parameters to produce particular affective cues rather than a single parameter. In addition, one function can be established to link the mood variable to these interrelated parameters as a group, while they link to each other internally by functions that describe their interrelations (Table IV). In our case, a link can be built between mood variables and the motion-speed, to which other parameters can be linked otherwise. Thus, research can be focused on the mapping from mood variables to multiple parameters as a whole instead of to each individual one.

VI. CONCLUSION

This paper presents our study on the relative importance of the behavior parameters and their interrelationships in a behavior model used for mood expression. Results indicate that the importance of each parameter is different, and thus it is possible to express moods by modulating only the important parameters. In our case, the parameters of spatial extent (amplitude and hand-height), the vertical position of the head, and the temporal extent (motion-speed) are the most important factors for expressing moods in *both* behaviors. These parameters are probably important for a variety of behaviors. However, this study covered only two behaviors. More behaviors need to be investigated to validate this point.

This study also shows that some parameters are interrelated and they should be modulated in combination to produce the behavioral cues that express a particular mood. From the perspective of designers, one function can be used to map mood variables to the interrelated parameters as a group. In this way, the robot system can also be simplified.

In the future we plan to conduct a recognition experiment, in which designed behaviors will be evaluated and whether the unimportant parameters can be removed without reducing the recognition rate of moods will be tested. Moreover, the importance suggests how easily moods can be recognized through the modulation of each parameter may be different. This will also be addressed in the recognition experiment. Furthermore, these design principles will be applied to more behaviors and evaluated in real HRI scenarios.

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