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Quantifying the Human Likeness of a Humanoid Robot

Joachim von Zitzewitz · Patrick M. Boesch · Peter Wolf · Robert Riener

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Abstract In research of human-robot interactions, human likeness (HL) of robots is frequently used as an individual, vague parameter to describe how a robot is perceived by a human. However, such a simplification of HL is often not sufficient given the complexity and multidimensionality of human-robot interaction. Therefore, HL must be seen as a variable influenced by a network of parameter fields. The first goal of this paper is to introduce such a network which systematically characterizes all relevant aspects of HL. The network is subdivided into ten parameter fields, five describing static aspects of appearance and five describing dynamic aspects of behavior. The second goal of this paper is to propose a methodology to quantify the impact of single or multiple parameters out of these fields on perceived HL. Prior to quantification, the minimal perceivable difference, i.e. the threshold of perception, is determined for the parameters of interest in a first experiment. Thereafter, these parameters are modified in whole-number multiple of the threshold of perception to investigate their influence on perceived HL in a second experiment. This methodology was illustrated on the parameters speed and sequencing (onset of joint movements) of the parameter field movement as well as on the parameter sound. Results revealed that the perceived HL is more sensitive to changes in sequencing than to changes in speed. The sound of the motors during the movement also reduced perceived HL. The presented methodology should guide further, systematic explorations of the proposed network of HL parameters in order to determine and optimize acceptance of humanoid robots.

Keywords Humanoid · Robot · Human-robot interaction · Uncanny valley · Human likeness

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1 Introduction

1.1 Soft interaction between humans and robots

In human-robot interaction, the primary goal is that the human subject can interact with the robot in a safe and intuitive way. This becomes possible if the robot behaves naturally, meaning that the human can intuitively interpret its actions and predict its reactions. Such natural interactive behavior of robots is a primary aspect in the field of soft robotics, as described by R. Pfeifer in a recent interview [1]: "The idea [of soft robotics] is, that robots, which humans will have to interact with, [. . .] move in a more natural and soft way."

However, not only their interactive behavior but also their appearance strongly influences the way how robots are perceived. Nowadays, it is already possible to build astonishingly natural looking, human-resembling robots such as Kobayashi's android teacher SAYA [2], Hanson's facial expression model EVA [3], or Ishiguro's android Geminoid HI-1 [4]. Despite their high level of human likeness (HL), some of these robots might still cause an eerie feeling in humans and, thus, might not be treated as familiar companions. This phenomenon can be explained by the so-called uncanny valley, first proposed by Mori [5]. The uncanny valley explains the relationship between perception of a robot by a human subject and the robot's HL. Mori states that the positive perception of a robot does not necessarily increase with increased HL of the robot [5] which is also confirmed in recent work, e.g. [6].

Despite the relatively long time since Mori published his paper, the uncanny valley effect is not fully understood yet. Some attempts were made to quantify the relationship for humanoid robots in general [7–9] or, more successfully, for particular aspects of humanoid robots, such as expressions [10], movements [11], or voice [12]. The general lack of concise conclusions, especially in studies on entire robots, lies in the fact that it is unknown which aspects of the robot are responsible for the observed effects. HL as a single parameter does not sufficiently describe the complexity and multidimensionality of this term. The work of Goetz et al. [13] points into this direction, proving that apart from visual appearance also parameters such as appropriate behavior influence the acceptance of humanoids. Hence, HL should be seen as a property of a robot defined by a multidimensional set of parameters. If the interaction between single parameters and their impact on the overall robot's HL is known, the relationship between robots' HL and the acceptance of robots by humans can be determined in a general manner.

1.2 Parameterizing the Human Likeness of Humanoid Robots

In this paper, we present an approach to identify and characterize the parameters of HL. In a first step, we suggest a network of parameter fields (NoPF) spanning the entire parameter space of HL. The suggested fields and parameters are based on an extensive literature research and on talks with experts. In a second step, we propose a general methodology to quantify the influences of the different parameters on the perceived HL of a robot as well as the mutual relationships between parameters.

Within this methodology, we first investigate the sensitivity of human subjects to perceive different settings of single parameters. Subsequently, a method to investigate the impact of different parameter settings on perceived HL is presented. We conclude the presentation of our method by exemplarily applying it to two parameters. The proposed NoPF together with the proposed methodology allow for a systematic research on HL and its perception. Knowing the relation between the parameters and their impact on HL will enable description and manipulation of the human perception of robots.

2 Parameters of Human Likeness

2.1 Parameterizing Human Likeness

HL should be parameterized in terms of all relevant aspects. HL, as used in this paper, represents how much the robot appears and behaves like a human.

As a start, we separate the NoPF describing HL into two categories common in humanoid robotics: appearance and behavior [14, 15]. *Appearance* is used to describe the static aspects of a robot. *Behavior* describes its dynamic aspects. Within these categories, we sort the parameters into so called *Parameter Fields*. Parameter fields associate parameters which describe a particular aspect of the robot. These parameter fields are not mutually exclusive and intersections may exist. In addition, parameters may influence different fields. In such a case, parameters may be assigned to several fields.

The parameter fields of appearance are given by the human senses perceiving static aspects of the robot: *Visual Appearance* by sight; *Sound* by hearing; *Smell* by smell; *Haptic Appearance* by touch; and *Taste* by taste. Visual appearance and sound are relevant from distance and in videos. Smell and haptic appearance become important for short distances, termed contact interaction. Taste is not considered in detail in the presented NoPF as it is not likely to become relevant to perceive a robot through taste in the near future.

In contrast to appearance, such an obvious classification into parameter fields is not given for behavior. However, humans move in some context (resulting in a behavior) or they communicate. Behavior can be interactive with the environment or of social nature. Humans can communicate either through language or by actions. Accordingly, we suggested the following five aspects as parameter fields of behavior: *Movement*, *Interactive Behavior*, *Social Behavior*, *Verbal Communication*, and *Nonverbal Communication*.

The parameter fields are arranged according to their importance for social interaction as well as to their primary interdependencies. Movement is a prerequisite for nonverbal communication (e.g. gestures or facial expressions), which in case of visual contact, is inherently linked to verbal communication. Verbal communication affects social behavior [16]. Social behavior goes hand in hand with interactive behavior, for which movement is a clear prerequisite. These interdependencies are again not of an exclusive nature.

Social behavior is seen as the pinnacle of behavioral appearance, because it builds on all other parameter fields and due to its advanced complexity (Fig. 1).

2.2 Parameter Fields of Appearance

2.2.1 Visual Appearance

Since most human actions are triggered by visual perception, the visual appearance of a robot is a crucial factor

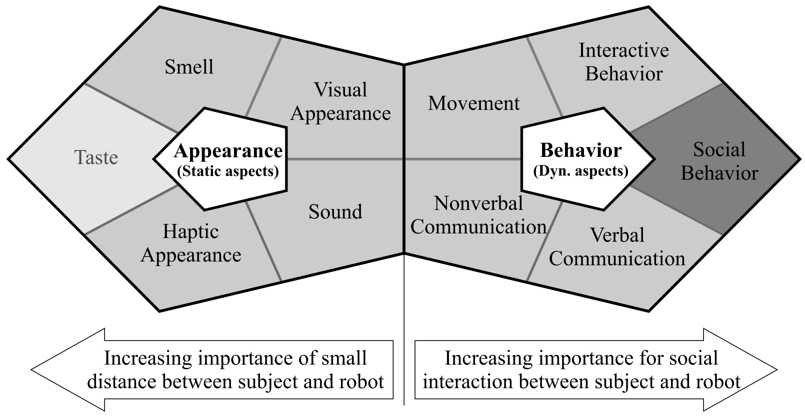


Fig. 1 Parameter fields of HL: The two categories of HL, *Behavior* and *Appearance* with their respective parameter fields. The parameter field *Social Behavior*, as the pinnacle of behavioral appearance, is highlighted with a darker color. The parameter field *Taste* is paled because it is not considered in detail in the NoPF. The *arrows* below the categories point into the direction of the parameter fields which require an increasingly smaller spatial distance between robot and subject (*appearance*) and which are of increased importance for social interaction between robot and human (*behavior*)

concerning the perception of a robot. Moreover, the visual appearance of robots has been proven to bias human-robot interactions [17]. Coeckelbergh [18] even states that "whatever the 'real' status of the robot may be, it is its [visual] appearance that is relevant to how the human-robot relation is experienced and constructed." Appearance-in-context [17] is the concept bringing this biasing effect of visual appearance to the point: as soon as the robot should be treated as a peer rather than a subordinate, human-like appearance is mandatory.

Various projects characterized the influence of visual appearance on the perception of robots. Topics are, for example, the perception of the overall appearance of robots [9] or the difference in perception of on-screen representations of artificial agents versus real life robots [19]. However, to our knowledge, none of them investigated the particular aspect of HL in detail.

2.2.2 Sound

The most important factor of a human's acoustic appearance is his or her characteristic voice. It is modulated by the human's mood, intention, and emotion. Artificial voices which sound natural in everyday situations are currently under development [20, 21].

Next to voice, important parts of the acoustic appearance are intentional and unintentional body sounds as well as interaction sounds occurring when a person mechanically interacts with his or her environment. Until now, these aspects have not been investigated in terms of robots' HL.

2.2.3 Smell

Smell is one of the most primitive sensory systems in humans and it has a very instinctive influence on our thinking [22]. Therefore, we assume that a robot's smell, although only perceivable at a short distance, might have a strong and direct influence on the emotional reactions towards the robot.

The influence of the smell of a robot on human-robot interaction and on the perceived HL of a robot has not been investigated up to now.

2.2.4 Haptic Appearance

Haptic appearance describes what a person should feel when he or she touches the robot. The relevant parameters considered to mainly describe haptic appearance are temperature, softness, and texture of a surface. The respective parameter settings are dependent on the particular part of the human body. For example, hair and skin are expected to have entirely different settings.

Realistic tactile properties of artificial skin are important for the development of cosmetic prostheses [5, 23]. Up to now, investigations on the haptic appearance of robots are restricted to haptic interactions between humans and robots [24, 25].

2.3 Parameter Fields of Behavior

2.3.1 Movement

Humans need only few cues to recognize movement patterns [26]. Given this sensitivity, it proves to be very challenging to produce convincingly natural appearing movements in robots or computer-animated avatars. Most humanoid robots are not able to reproduce natural, human movements. Consequently, people are still stunned if a robot, like for example Sony Qrio, manages to show convincingly natural movements.

To perceive robots as human-like, a realistic, i.e. human-like, movement of the robot is of major importance [10, 27, 28]. The importance of movement is reflected in a recent study by Kamide et al. [29], in which test subjects had to rate their impressions of a humanoid robot on a psychological scale by simply watching it walk.

2.3.2 *Nonverbal Communication*

Nonverbal communication consists of facial expression, gesturing, proxemics, eye contact, imitation, and stigmergy. It supports and enriches verbal communication [30–32]. It is able to replace verbal language to large extent, especially for communication of simpler information, for giving social cues or for the conveyance of emotions and intentions [33].

Simple nonverbal communication, e.g. a restricted library of gestures, provides a convenient way for robots to communicate successfully with humans. This kind of nonverbal communication is already in intensive use in social robotics as summarized by Fong et al. [17], Kanda et al. [33], or Ritter et al. [34].

2.3.3 *Verbal Communication*

Natural language is far more complex than written language or even non-verbal communication. Human speech conveys not only the content of what was said. The content is influenced also by the way it is expressed and by the person, who speaks [35]. In addition, speech is often grammatically incorrect and information carried by the words is incomplete. Only in the combination with the other two factors of speech—how and by whom—it becomes sensible [36].

Such a holistic understanding of speech is apparently not to be mastered artificially in the near future. This explains why, apart from a few exceptions [37–39], natural language has played a limited role in human-robot interaction so far.

2.3.4 *Social Behavior*

The parameter field *Social Behavior* incorporates everything on how the robot is expected to interact with other entities, such as humans, animals, or other robots.

A definition of social robotics was given by Dautenhahn et al. [40]: "Social robots are embodied agents that are part of a heterogeneous group: a society of robots or humans. They are able to recognize each other and engage in social interactions, they possess histories (perceive and interpret the world in terms of their own experience), and they explicitly communicate with and learn from each other."

Yet, advanced *Social Behavior* requires the implementation of a so-called *theory of mind* in the robot enabling it to perform e.g. cognitive developmental processes [41, 42]. As a corresponding universal implementation methodology is still an open research question, *Social Behavior* can be considered as the most complex parameter field to be investigated and can be considered the pinnacle of human-robot interaction.

But once social behavior is achieved, the robot appears alive as Turkle points out [43]: "If an entity makes eye contact with you, if an entity reaches toward you in friendship, we believe there is somebody there...".

2.3.5 *Interactive Behavior*

Following Johnston and Pennypacker [44], we define interactive behavior as any detectable move by an acting entity that leads to a measurable change in the environment. We further extend the definition by including any detectable change in an acting entity's behavior caused by the environment.

In robotics, interactive behavior is traditionally achieved by supplying the robot with a limited library of basic behaviors, from which one is chosen based on the robot's present state and the present sensory stimuli. Kanda et al. [33] suggest that a large set of basic behaviors available to a robot can positively influence the perception of the robot. Mataric [45] listed a few interactive behaviors considered as standard robotic capabilities, including: obstacle avoidance, navigation, terrain mapping, object manipulation, and walking.

2.4 Characteristics of Parameter Fields

Each parameter field is characterized by general field parameters and by possible subfields. Each subfield consists of further parameters and, possibly, of further subfields. The subfields themselves are influenced by other field parameters or subfields. A list of identified parameters and subfields for each parameter field can be found in Table 1.

To give a deeper insight into a single parameter field, the parameter field *Movement* is presented in more detail. *Movement* can be subdivided into the groups of *Basic Movements* and *Associated Movements* (Fig. 2). Six field parameters and seven subfields were identified, which can characterize both of these movement groups. The field parameters are *Speed*, *Fluency*, *Stiffness*, *Range of Motion*, *Complexity*, and *Spatiotemporal Variability*, and the subfields are *Sequencing*, *Velocity Profile*, *Physiological Correctness*, *Precision*, *Efficiency*, *Appropriateness*, and *Situatedness*.

In Appendix, a short explanation and a suggestion of quantification is given for each identified subfield and parameter in the parameter field of *Movement*.

2.5 General Hypothesis

Related to the NoPF, the following hypotheses are formulated:

Table 1 Subdivision, parameters, and subfields of parameter fields

	Subdivision	Parameters	Subfields
Visual appearance	Skin, hair, body, face, clothing	Shades, reflexions, transparency, size, color, form, arrangement	Movement behavior
Sound	Voice, interaction sounds, body sounds	Volume, pitch, timbre	Appropriateness, situatedness
Smell		Strength	Kind of smell, smell of body, appropriateness
Haptic appearance	Hair, skin, body	Temperature, softness, movement resistance	Surface structure, micro-movements
Movement	Basic movements, associated movements	Speed, fluency, stiffness, range of motion, complexity, spatiotemporal variability	Sequencing, velocity profile, physiological correctness, precision, efficiency, appropriateness, situatedness
Verbal communication	Kind of language, phenomena of correction, sequencing signals, turn-taking	Intelligibility, processing delay, engagement	Emotions, appropriateness, situatedness
Nonverbal communication	Facial expressions, gestures, proxemics, eye contact, body contact, posture, vegetative symptoms	Expressiveness, engagement	Emotions, appropriateness, situatedness
Social behavior	Image cultivation, group behaviors, stigmercy, morality, base behaviors, key stimuli, binding ability, user modeling, attention, imitation	Goal orientation, aggression, politeness	Emotions, appropriateness, situatedness
Interactive behavior	Orientation, sense of time, base behaviors, group behaviors, instinctivity	Goal orientation, aggression, care	Emotions, appropriateness, situatedness

– Each identified parameter has an influence on the perceived HL of a robot. A (nonlinear) function describes this influence.
– The functions of different parameters are coupled. Two parameters are expected to amplify each others function of perceived HL. This means that the quality of one parameter affects the function describing another parameter.

3 Methodology

3.1 General Method to Characterize Parameters of Human Likeness

In this part, we propose a method to determine the perception profiles of the parameters of HL. A perception profile is a (nonlinear) function which describes how a change in a parameter changes the perceived HL of the robot.

In a preparatory experiment, the minimal (by a human) perceivable change in a parameter has to be determined (Sect. 3.1.1). Thereafter, the impact of different parameter settings on the perceived HL is evaluated (Sect. 3.1.2).

3.1.1 Determining the Threshold of Perception

A threshold of perception (ToP) is the minimal difference between two parameter values which is still perceivable by a human observer. It therefore defines the minimal unit of the related parameter scale. This kind of definition for the parameter scale is supposed to normalize the scales of different parameters to facilitate comparisons between different parameters.

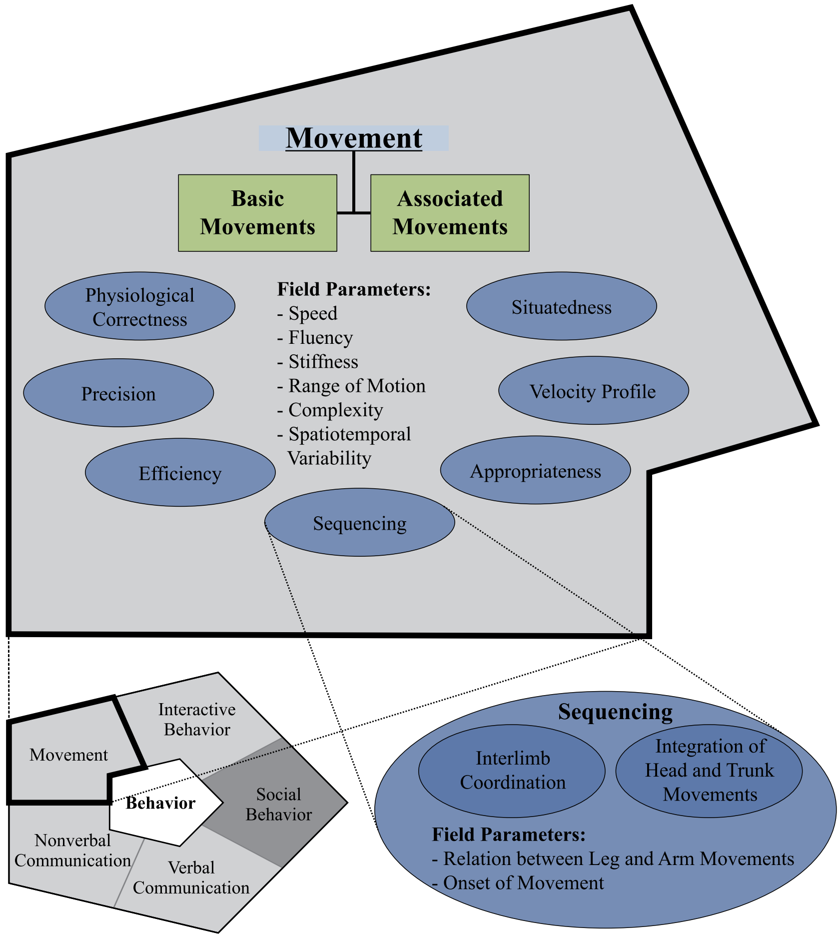
The ToP for a parameter is identified by comparing presentations which slightly differ in this parameter only. The ToP is then given by the minimal difference in parameter values that at least 90 % of all subjects perceive.

3.1.2 Determining the Perception Profiles

In this step, the perceived HL of the robot is identified for different parameter settings demonstrated to a human test subject. The demonstrated parameter settings are centered around the optimum of the parameter. The optimum is the human average for this parameter, which is either known from literature or is to be determined from own experiments/experiences.

The optimal parameter setting defines the basic demonstration. Other demonstrations are defined by parameter settings which differ from the optimum in at least one time the ToP of the parameter under investigation. The difference is termed *distance to optimum* and should be a whole-number multiple of the related ToP. An exponential scale is used for the whole-number multiples in order to combine a detailed

Fig. 2 Overview of the parameter field *Movement* (subfields inside dark ellipses)



analysis of the parameter influence close to the optimum with an investigation on the broad influence of the parameter.

Once the above mentioned set of demonstrations is defined, it is evaluated. In an evaluation of a demonstration, the respective HL of the robot as perceived by humans is determined. A possible method to determine the HL is to (in some form, e.g. live or video) present the demonstrations to human observers and let the observers rate the perceived HL. The order in which the demonstrations are evaluated must be randomized. Through this evaluation, a perceived HL is allocated to each parameter setting. From that, a *Perception Profile* can be identified for each parameter, which is the goal of the method.

3.2 Experimental Evaluation of the Proposed Method

3.2.1 Hardware and Methodology

To determine how perceived HL depends on changes inside a parameter field, we exemplified the application of our proposed methodology on the parameter speed and the subfield sequencing of the parameter field movement.

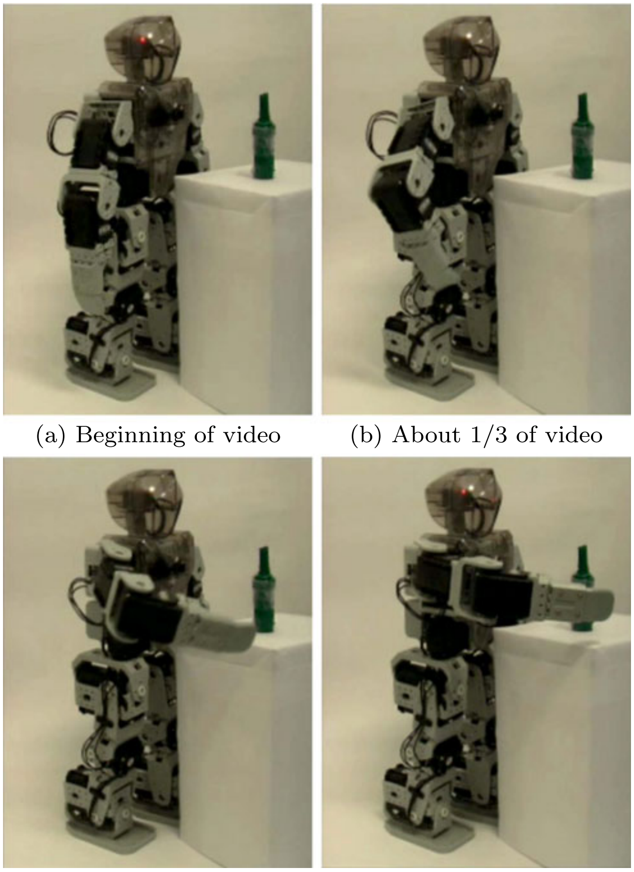
To exemplify also the impact of a parameter of another field on the above selected parameters of HL, sound was chosen. All three parameters were easy to adapt on the used robotic platform.

The robot (Fig. 3) used in this evaluation is a *Robotis Bioloid Premium Humanoid Type A* by *Robotis Co., Ltd.* specified by Teodoro [46]. The robot was controlled through MATLAB® using the *USB2Dynamixel* hardware interface and the accompanying *Dynamixel SDK API*. For the experiment, a grasping movement of the robot with different parameter settings was recorded by video. This movement was recorded on video for different settings of the parameters investigated.

3.2.2 Parameters Under Investigation

The field parameter *Speed* and the subfield *Sequencing* are explained below as they are later used to illustrate the application of our proposed methodology to investigate the influence of single parameters on perceived HL.

Sequencing *Sequencing* involves the field parameters *Onset of Movement* and *Relation between Leg and Arm Movements* as well as the subfields *Interlimb Coordination* and



(a) Beginning of video (b) About 1/3 of video

(c) About 2/3 of video (d) End of video

Fig. 3 The humanoid robot in use, as presented in the experiment. Showing a movement of 2.06 seconds, the total duration of the video was 2.68 seconds

Integration of Head and Trunk Movements [47]. *Sequencing* is positively correlated to *Fluency*, *Efficiency*, *Appropriateness*, and *Associated Movements* [48].

Since *Sequencing* constitutes a subfield of parameters, a direct quantification of *Sequencing* is difficult. Rather, subparameters of *Sequencing*, for example *Onset of Movement*, have to be quantified and the results should be integrated to a quantification of *Sequencing*.

The subfield *Sequencing* is evaluated through one of its parameters, *Onset of Movement*. For a given trajectory of the total body movement, *Onset of Movement* defines for each involved actuator the point in time to start the movement. The implementation of the minimal hand jerk principle [49] resulted in a movement of all involved actuators in parallel, from the beginning to the end of the movement.

In the experiment, beside the *Onset of Movement*, the *Sequencing* profile was varied from 'all parallel' defined as 0 % to 'all serial' defined as 100 %. The percentage value refers to the shift in starting time of the single axis relative to the duration of the 'all parallel' movement. This value can be continuously shifted. For reasons of simplification, we will stay with the term *Sequencing* in the upcoming explanations.

Speed The parameter *Speed* describes the average speed of a movement. When the displacement is known, *Speed* can be quantified by the total duration of a movement. This holds true for robotic movements when movement path including start and end point are predefined.

The parameter *Speed* can be modified from faster than natural to slower than natural. No clear human optimum for *Speed* exists. We estimated 1.5 internal time units (ITU) (2.06 seconds) to be the optimum duration for the movement task performed by the robot (Sect. 3.2.4, subsection *Videos*). To get this estimation, a human subject was asked to perform a similar grasping task and the execution time was measured.

Sound In the experiment, we focus on the sound of actuators. Without interaction, the human musculoskeletal system works silently. Therefore, the human optimum is no sound during movement.

In the experiment, we presented the robot with and without sound of actuators.

3.2.3 *Working Hypothesis*

We hypothesize about the mutual influences between *Sequencing*, *Speed*, and *Sound*, that:

- *Sequencing* and *Speed* amplify each other's perception profile: The closer a parameter setting is to the optimal parameter setting, the higher the perceived HL is.
- The presence of *Sound* reduces the perceived HL on the perception profiles of *Sequencing* and *Speed*.

3.2.4 *Thresholds of Perception*

Twelve videos were sent to a group of eleven subjects (five females, six males, aged from 20 to 50 years) showing two subvideos simultaneously. Both subvideos presented the same robot in the same environment doing the same task.

The subvideos only differed in the parameter setting of either speed or sequencing. One of the subvideos always showed the optimal, most human-like parameter setting for both parameters.

In sequencing the minimum presented difference was 1 % of the total range of sequencing; total range in the sense of at 0 % all robot servos move in parallel (optimum) and at 100 % all servos move in series.

For speed the minimum presented difference in total duration was 0.1 ITUs (0.14 seconds).

The subjects were asked to decide for each video whether a difference between the two videos was perceivable or not. The videos were presented in randomized order.

Table 2 Videos shown to the participants (x: video shown once; o: videos shown once with and once without sound; /: videos shown twice without sound for reproducibility, %: videos shown once with sound and twice without sound for reproducibility

Seq. [ToP]	Speed[ToP]									
	−2	−1	0	1	2	3	5	7	11	19
0	x	o	x	x	x	x	o	x	o	x
1			x							
2			%				/			o
3	x		x		%			%		
4			o			/			x	
5			x				%			x
7	o		x		x			x		
9			%			%			o	
11			x				o			x
12.4	x		x		x			x		

3.2.5 *Perception Profiles*

After the tresholds of perception were determined, an online survey was prepared presenting different videos of the robot doing the same task. In each video, the robot did the task with a different parameter setting. The subjects were asked to rate each video on their perceived HL of the robot's movement.

Videos The videos recorded for the online survey showed the robot reaching for a bottle (Fig. 3). The robot starts from a neutral position and the bottle stands on a table in front of the robot.

For all videos the same robot was used and the background, the light, and the position of camera were kept the same. In total, 38 videos were recorded: To evaluate the perception profiles of speed and sequencing, we demonstrated ten different parameter levels each (distances to the optimum). During these demonstrations, the other parameter was kept at its most human-like level. The remaining 18 videos were recorded to characterize the parameter space between speed and sequencing. They demonstrated different combinations of parameter settings. Additionally, eight randomly chosen videos were shown twice to test for reproducibility. Furthermore, another 14 videos were shown with sound. This resulted in a total of 60 videos to be presented (Table 2).

Online Questionnaire For the experiment, we used the online questionnaire suite *EFS Survey* by Unipark. The demonstration of the 60 videos occurred in randomized order for every subject. For every video, the subjects were asked to rate the HL of the observed movement by answering the question "Does the robot behave as you would expect it from a human?" They could rate it on a horizontal slider bar. The 10-step-scale ranged from 'Mechanical' (1) to 'Human' (10). To account for the large number of videos to rate, the questionnaire was held as simple as possible presenting only one question.

Subjects Eleven females, 14 males, aged from below 20 to above 50 years, majority between 20 and 29 years, participated in the survey. None of the subjects knew about the parameters under investigation and they did not see the videos before the survey.

Statistical Analysis In the analysis of the reproducibility of our method, we follow an approach by de Vet [50]. We accept a tolerance of 10 % on reproducibility. Given a ten step scale, this means that if the answer on the repeated question is within 1 unit of HL of the original question, they are counted as consistent answers. For the individual reproducibility, we calculated the percentage of consistent answers from all eight repetitions for each subject. The reproducibility of our method is the average of these individual reproducibilities.

To evaluate the influences evoked by sound, we took the mean of the differences of perception for each subject over all 14 video combinations 'sound—without sound'. On all means of the whole population, we applied a two-sided sign test (null hypothesis "continuous distribution with zero median", and alpha at 5 %).

4 Results

4.1 Preparatory Experiment—Thresholds of Perception

In the preparatory experiment, all subjects were able to determine a difference between two subvideos at individual thresholds. The ToP for sequencing is 7 % of the total range of sequencing. The ToP for speed is 0.4 ITUs (0.56 seconds) (Table 3).

4.2 Main Experiment—Perception Profiles

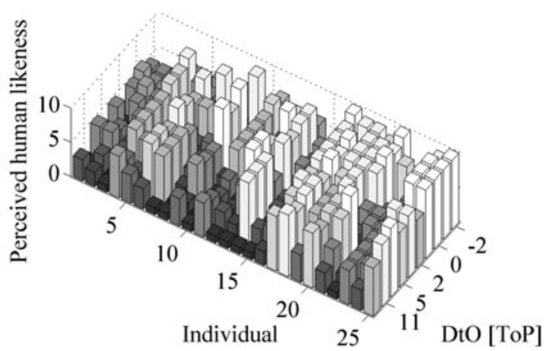
The reproducibility of our methodology was 67 % with a standard deviation of 24 %.

4.2.1 *Individual Perception Profiles*

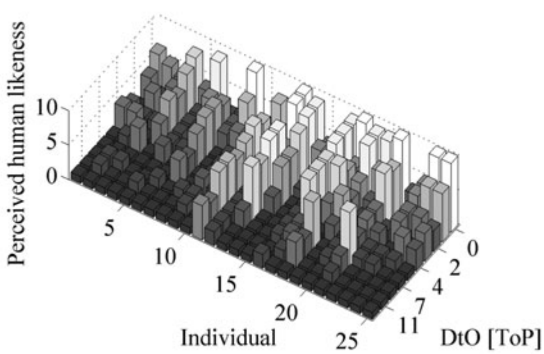
Among the different subjects, several, repeatedly occurring types of rating profiles can be observed (Fig. 4). One such repeatedly occurring profile consists of a consistent rating for all videos, for example the profile of subject 20 of speed. Another repeatedly occurring profile shows one single very steep increase at a certain point, for example the profile of subject 25 of sequencing. A third example for a repeatedly

Table 3 Thresholds of Perception. In bold is the difference which was perceived by 90 % or more of the subjects

Sequencing	Difference in sequencing	1 %	2 %	3 %	4 %	**7 %**	9 %	14 %
	Subjects perceiving a difference	0 %	0 %	64 %	45 %	**91 %**	100 %	100 %
Speed	Difference in total time [ITU]	0.1	0.2	0.3	**0.4**	0.5		
	Subjects perceiving a difference	0 %	64 %	73 %	**100 %**	100 %		



(a) Speed



(b) Sequencing

Fig. 4 Individual perception profiles of Speed and Sequencing. Subjects differ in brightness. DtO means 'Distance to Optimum'

occurring profile is the profile of subject 14 of sequencing, displaying several distinct shifts.

Among subjects, different absolute values of the perception profile can be observed (e.g. mean difference of 3.8 between subject 20 and 23), while the profiles are similar (standard deviation of difference of 1.3).

4.2.2 Average Perception Profiles

The profile of the parameter speed decreased much less and is spread much wider than the sequencing profile (Fig. 5a). Starting from maximal distance to optimum, both parameter profiles show firstly a trend towards more HL. Then a short plateau is apparent which is followed by a further increase to the most human-like parameter state. This most human-like state consists of one single parameter value for sequencing respectively of a saddle of three equally high parameter values for speed.

The percentiles spread over several units of HL, thus, showing a high interpersonal variability concerning the profiles.

4.2.3 Spanned Parameter Space

The single parameter profiles for speed and sequencing are supported by the space spanned by the two parameters (Fig. 5b). The moderate decrease in HL (less than 0.2 per ToP) with increasing distance in speed is visible in the figure and supported by the measurements in which both parameters were changed. A similar confirmation is observable in the direction of sequencing. The steep fall of almost 1 point of HL per ToP followed by a flat but low area is supported by the whole space. The only exception standing out is the perceived HL for a sequencing of 7 and a speed of 0.

A very high value of HL is never reached. Even the top states remain at a HL of about 6.5.

4.2.4 Influence of Sound

Across the whole population, the robot was perceived in average about 20 % less human-like when the sound was switched on and the subjects could hear the sound of the motors (Fig. 6). If the average perceived HL without sound was two units of HL or less, the perceived relative shift was less than 20 %.

5 Discussion

5.1 General Applicability

Until now, HL has been considered as one parameter to be set, which would cause a certain perception of the robot. However, such a consideration does not allow to describe and understand HL in detail. Therefore, we defined HL as a variable dependent on a NoPF. Our presented NoPF is based on common fields of robotics (appearance and behavior) and systematically further subdivided; in particular, the subdivision of the parameter field movement is exemplified. This example should provide an idea, how detailed the NoPF could be.

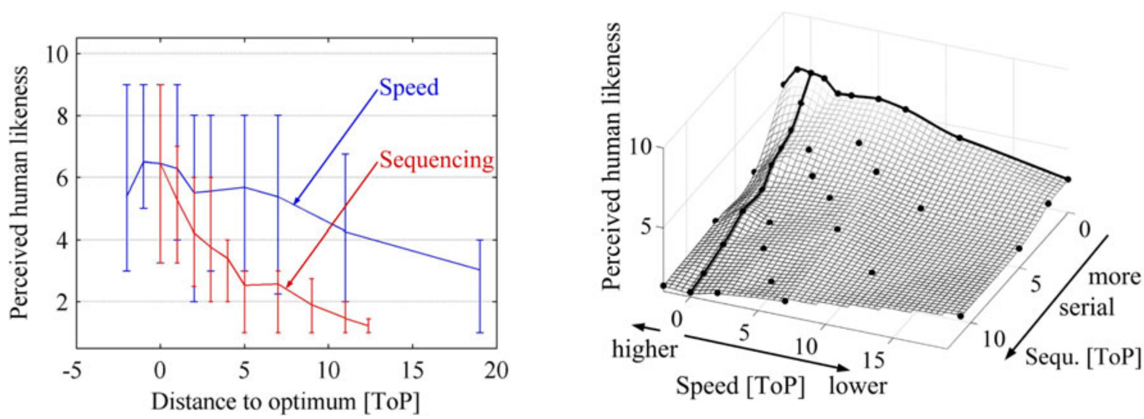


Fig. 5 Perception profiles of HL. (*Left*) Average perception profiles of speed (*blue*) and sequencing (*red*). For each investigated level of speed and sequencing, the average and two percentiles are shown. The presented percentiles are the 25th (below average) and the 75th (above average). (*Right*) Parameter space spanned by speed and sequencing. The *black dots* indicate measurements. The *black lines* equal the two perception profiles for speed and sequencing presented on the left. The mesh is a cubic interpolation of the measurements. The mesh brightness—from dark to bright—indicate increasing perceived HL (Color figure online)

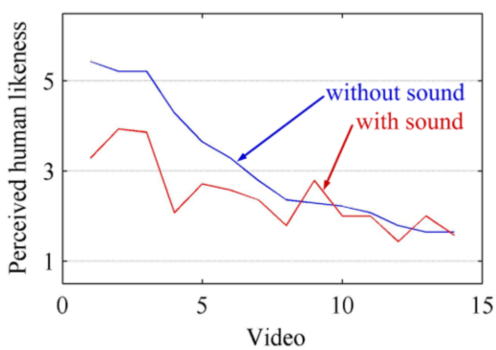


Fig. 6 Influence of sound on the perceived HL. Along the x-axis, the videos are ordered with decreasing average perceived HL without sound, which is represented by the *blue curve*. Represented by the second curve (*red*) is the respective average perceived HL with sound (Color figure online)

Our proposed methodology is based on video presentations which easily provide a determination of the threshold of perception for each parameter of interest. In future, such videos may even be replaced by computer animations, which make the whole determination as well as the investigation of the impact of single parameters or a combination of parameters even simpler. One should be aware that there can be differences in perception of virtual robots and real robots [29].

The proposed identification of the ToP gives a clear hint up to which extend single parameters can deviate from the optimum before a human subject perceives it. The thresholds can serve as a guideline for designers indicating which level of imperfection is tolerable.

By systematically modifying a single parameter or a set of parameters by multiples of the ToP, its or their effect on HL can be demonstrated. By modifying not only within a field of parameters (in this paper, speed and sequencing) but also by modifying a parameter of another field (sound), we have demonstrated that different parameter fields interact with each other. We would like to encourage future studies to explore parameters of different fields in order to provide a broader view on HL than in former studies. The systematic evaluation of single parameters and parameter sets of HL will help to identify which parameters have a major impact on HL and therefore, on human acceptance of robots.

5.2 Thresholds of Perception

The subjects had to decide which subvideos *clearly* differed. Thus, an overestimation of the ToPs was expected. This overestimation was accepted for the same reason, for which also a refinement of the presented scale was neglected: As the design of the main experiment required parameter gaps of at least one ToP, a slight overestimation of the real ToPs was useful.

5.3 Perception Profiles

In this paper, two parameter profiles of HL and the influence of a third parameter from a different field on these profiles were determined. From the comparison of the two profiles in Fig. 5a, we can draw the following conclusions: if you want to make your robot more human-like, a proper sequencing is much more important than a proper speed of movements. Only a slight deviation from optimally human-like sequencing results in huge drop of perceived HL of the movement. The speed profile, on the contrary, even showed some tolerance on the top level and with more deviance from the optimum, the drop in HL was very moderate.

This means that humans have a high tolerance towards the speed of movements while being very sensitive to sequencing. A high tolerance on speed was expected because speed of movement is very situation-dependent and in humans, a large variety of different speeds is generally accepted for the same situation. For sequencing the low tolerance was expected because sequencing is a very apparent feature of movement and a non-human sequencing results in the typical robot movements sometimes imitated by human dancers or street artists.

Concerning the perception profile, an exact choice of the parameter optimum is not required. The real optimum is obtained from the perception profile anyway, e.g. the speed optimum was very well estimated in our case (+1 ToP, Fig. 5a).

A striking feature of our results is the very large range over which the perceived HL was spread (Fig. 5a). This variability of perceived HL could be explained as follows: Two subjects may have a similar profile but at different absolute levels of HL, as mentioned in the results. In such a case the average represents the underlying distribution well despite a high variance. Based on this explanation we are convinced that the average perception profile represents well the underlying distribution despite the large spread.

The amplifying relation between the two parameters of movement as hypothesized in Sect. 2.5 is well apparent (Fig. 5b). The general trend given by the two perception profiles was supported nicely by the measurements on combinations of different parameter values.

The hypothesized, negative influence of sound on the perception profiles of the movement parameters was also confirmed. This finding is consistent with several authors' statements on the strong degree of interdependence between the two main categories of HL, appearance and behavior [8, 13] and illustrates the importance of including both categories in HL studies. The less negative shift towards larger distances to the optimum is explained by the already low perceived HL without sound in these cases. The clear negative amplification explains the low absolute HL obtained from the experiments: With the used robot and the chosen movement, the maximal average perceivable HL is only about 6.5, as shown in the results. The use of a different robot with e.g. a more human-like visual appearance would most probably have increased the perceived HL for the same movement parameters. Following our general hypothesis, we assume this is due to the unknown negative influence of other, unquantified parameters. For example, we expect the negative shift influence of the rather mechanical visual appearance of the robot to be immense.

The confidence in our method is good, but not overwhelming, given the reproducibility of 67 %. We explain this result with the large number of videos presented to each subject. Such a large number of demonstrations results in two effects. Firstly, with many videos the subjects becomes familiar with the videos, which in turn means that the answers become more accurate. Secondly, the increased familiarity results in different ratings in later stages of the survey. This results in a lower reproducibility. To investigate these effects, the study was repeated with different participants and a smaller number of videos (18 instead of 60, no "sound" conditions). As this study fully confirmed our results, we decided to present the more comprehensive data set. However, we suggest using fewer videos to increase the confidence in the method.

6 Conclusion

The perception of robots plays a crucial role in human-robot interaction. The suggestion of an uncanny valley by Mori [5] was a first attempt to characterize the relationship between perception and appearance. Even though the idea was never proven, those who work on the interface between humans and artificial agents have from experience the impression that at least some truth lies behind the idea. Investigations in the field often delivered only very limited results because HL was seen as one parameter.

The main idea presented by this paper is to see HL not as a single parameter but rather as a variable influenced by many other parameters. The impact of each parameter on perceived HL can be identified experimentally, given a structured methodology.

The methodology presented herein results in a map of HL for the parameters speed and sequencing. This map is a first example of how we imagine the use of our NoPF. A multitude of characterized parameters of HL spans a parameter space. For a desired HL, an appropriate parameter setting can be selected based on this map. Such a map could be useful for robotic scientists as well as for artists working in the field of movie animation or in game industries.

Our new understanding of HL enables us to view the uncanny valley from a new perspective. We suggest that the uncanny valley occurs when a majority of parameters of HL has crossed their threshold of non-human to human, while a minority of parameters is not on the appropriate level yet. In this situation, the artificial agent is seen as a human due to the majority of parameters suggesting a human, while the other parameters influence the perception negatively. By identifying these thresholds for the parameters of HL, the uncanny valley could be avoided in future. However, the laborious task of fully characterizing and quantifying the NoPF cannot be done by a single research group. Only if everybody in the community helps with his field of expertise, the problem identified by Mori about 40 years ago could be solved.

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Appendix: Movement Parameters

• ***Basic Movements:*** *Basic Movements* are single movements which cannot be further separated. Complex human movements are build by combining basic movements. This assumption has broad support in science, for example in movement sciences [51], or when movement primitives serve as a foundation for imitation learning [52–54].

• ***Associated Movements:*** The parameter *Associated Movements* is used for assessing human movements [48]. Association of movements exploits synergies of joints or physical effects to increase the efficiency of the overall movement.

• ***Fluency:*** *Fluency* is a typical parameter used to assess human movement [47, 48]. It is defined as the smoothness of a movement [47].

• ***Stiffness:*** Humans are able to modify the stiffness of a body part by simultaneously contracting the protagonist and the antagonist muscle [55].

• ***Range of Motion:*** *Range of Motion* is about the realism of movement constraints. It is a classic parameter of movement on joint limits and torque limits [49, 55].

• ***Complexity:*** Most human movements can be achieved involving different numbers of degrees of freedom (DoF). The complexity of a movement increases with the number of DoFs involved. The upper limit is maximum number of DoFs available for a movement. For example the maximum complexity achievable by a human hand is 27 DoFs [56].

• ***Spatiotemporal Variability:*** *Spatiotemporal Variability* is another typical parameter of human movement [47, 57]. Kakebeeke [47] defined it as the “variation in displacement, speed and rotation.”

• ***Velocity Profile:*** *Velocity* is a predominant quantitative parameter of human movement [48]. The velocity profiles of typical human movements show approximately the shape of a bell [49, 58, 59]. Robot movements, in order to resemble human movements, should show the same velocity profile.

• ***Physiological Correctness:*** An illustrative example to explain *Physiological Correctness* are the unfamiliar movements of people who are not able to use certain joints or muscles. The problem of low *Physiological Correctness* is also known in computer animation [55].

• ***Precision:*** Humans are able reach very high precision in movements when the movement is fine. However, even if the movement is fast or under high load humans are able to carry it out with precision. How capable is the robot in this respect?

• ***Efficiency:*** *Efficiency* is a parameter used in the assessment of human movements [48, 60]. It is defined as the “minimal motor activity for a task” [60].

• ***Appropriateness:*** *Appropriateness* describes whether the observed movement seems appropriate from a human’s perspective or not. To give an example, imagine a man strolling through the city on a sunny day. A high value of *Appropriateness* would have the man comfortably walking down the avenue.

• ***Situatedness:*** *Situatedness* relates the movement to the situation and the environment. A high value of *Situatedness* means that the movement is very well adapted to the current situation [48]. A situated movement is an efficient and safe movement to do in the given situation [55].

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