Emotional Gripping Expression of a Robotic Hand as Physical Contact

46193148

趙　哲宇

Contents

Abstract

This research aims at the emotional expression of a robotic hand through various gripping manners on the user's hand. The proposed system is implemented with a robotic hand's various haptic actuators to realize the change of the fingers' gripping force and the robotic hand's holding duration so that the user can haptically estimate the emotion of the robot. The system is expected to provide stress relief or emotional stability, especially for elderly or challenged people.

Contents

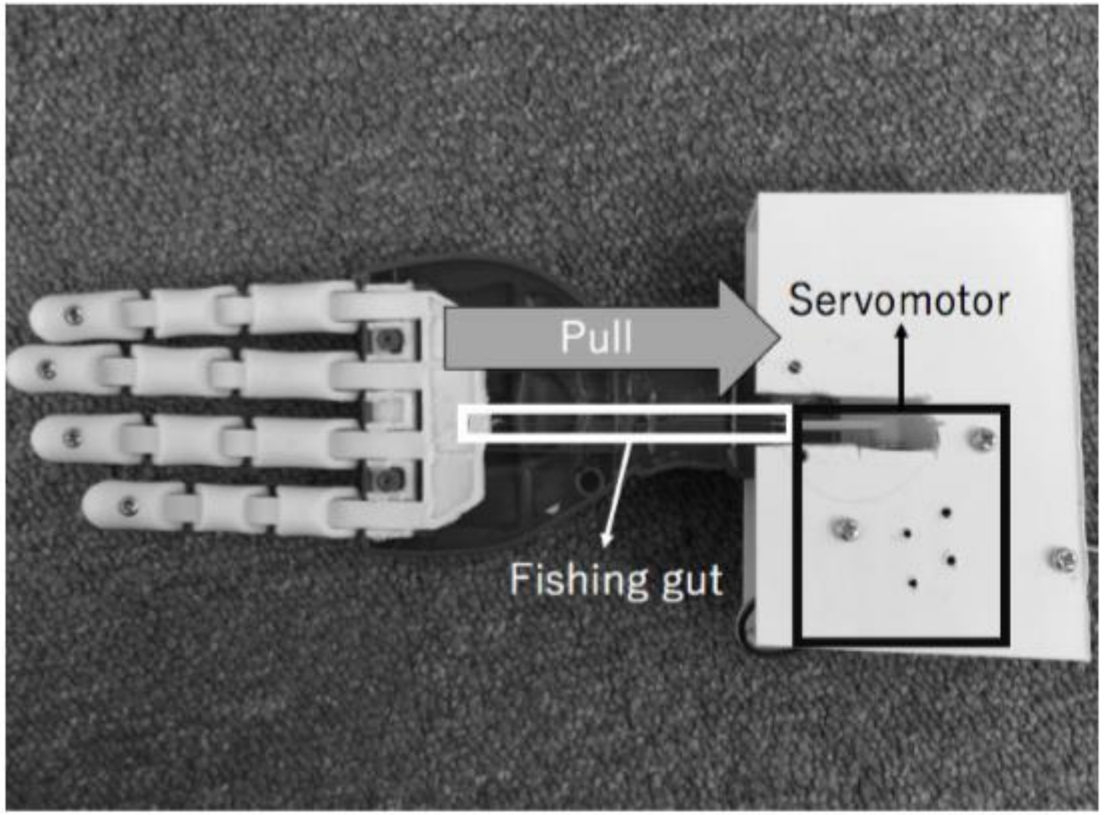

Figure 1: Configuration of the robotic hand

System Overview

The system consists of a PC, a robotic hand, an AVR controller, and a servomotor. The gripping strength of the robotic hand was simply changed by a servomotor which is controlled by the PC via the AVR controller. The timings of the gripping / release action were decided by the hand-holding duration. Currently, the two parameters of the gripping manner were directly controlled by the designed patterns. To automatically control the expressions corresponding to the robot's internal state and the user's demand, They verified the relationship between the gripping manner and the emotional expression of the robot in this paper.

System Evaluations

Factor A: The **strength** with which the robotic hand grips the user's hand(A):

Weak(40degrees) ordinary(60degrees) strong (80 degrees)

Factor B: The **duration** for which the robotic hand grips the user's hand(B):

Short(0.8seconds) normal(2.5seconds) long (4.5 seconds).

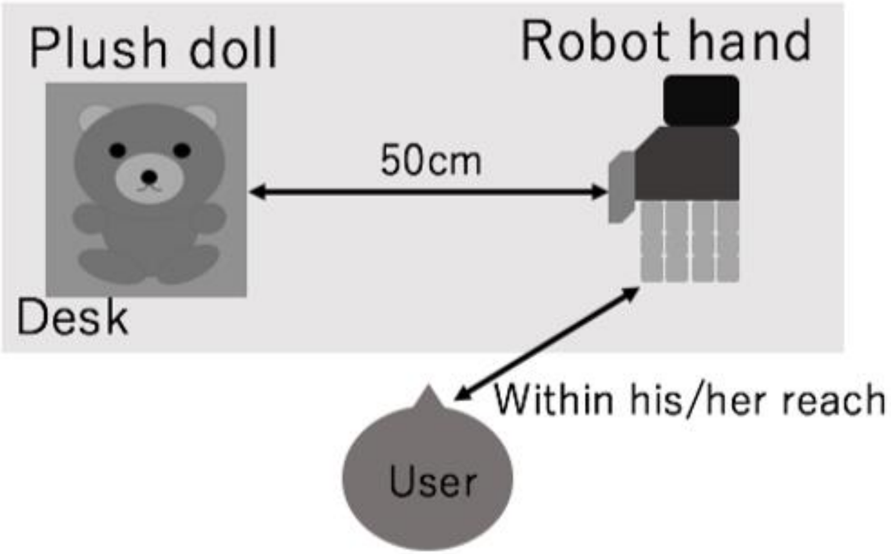

Figure 2: Experimental environment settings

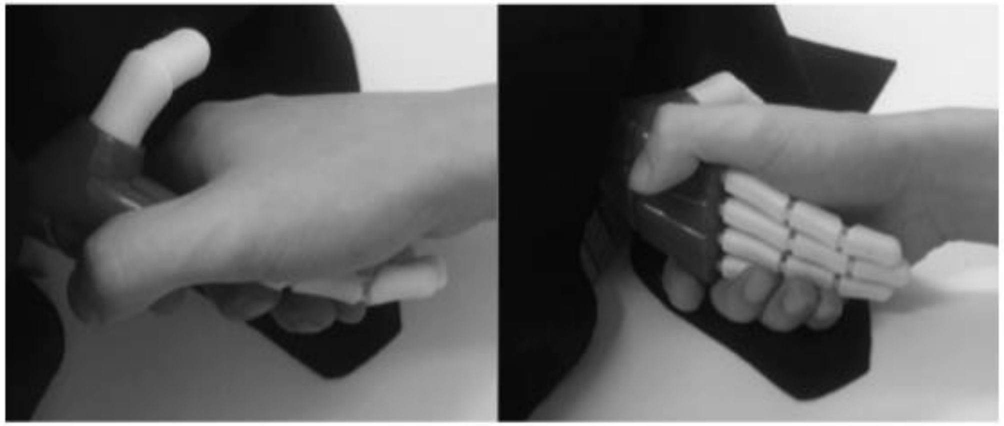

Figure 3: How to hold the robot hand

Procedure

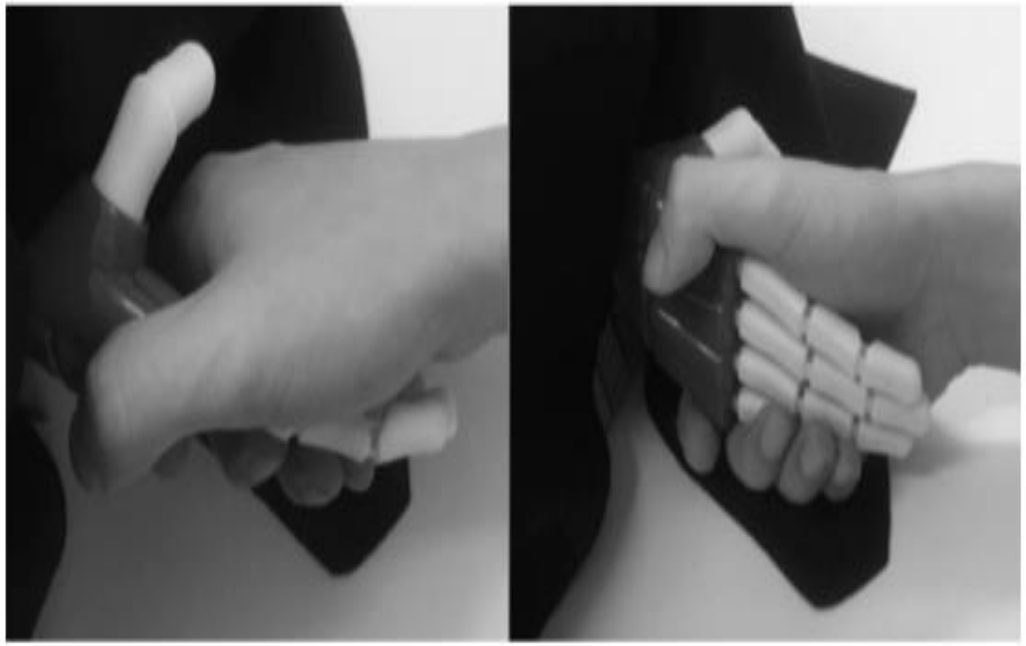

Figure 3: How to hold the robot hand

Procedure

The dialog between the bear and A-chan was started after the participant held A-chan's hand. The content of the dialog simulated a scare scene for the robotic hand to express strong emotion as follows.

Bear: "Hey, hey, hey, can you see IT?"

A-chan: "What do you mean IT?"

Bear: "Behind you....There is an ogre."

After the dialogue, A-chan gripped the participant's hand based on the experimental conditions and releases the participant's hand after the decided period for each condition.

Evaluation Statements

Table 1: Factor matrix (Varimax rotation)

j. pairs (1–5)	Factor1	Factor2	Factor3	Factor4
ensitive–Sensitive	**0.813**	0.154	0.170	0.013
w–Fast	**0.779**	0.141	0.135	-0.126
guely–Clear	**0.768**	0.202	0.221	-0.198
shonest–Honest	**0.642**	0.050	0.035	0.034
ll–Funny	**0.631**	0.301	0.202	0.221
ıpid–Smart	**0.620**	0.017	0.436	0.230
ring–Interesting	**0.614**	0.327	0.328	0.234
scure–Luculent	**0.602**	0.394	0.396	-0.100
pressed–Unfastened	**0.541**	0.440	0.039	0.342
or–Rich	**0.516**	0.443	0.229	0.358
rk–Bright	0.430	0.328	0.373	0.357
chanical–Human	0.168	**0.842**	0.125	0.025
natural–Natural	0.301	**0.765**	0.192	0.092
friendly–Friendly	0.286	**0.761**	0.349	0.080
approachable–Accessible	0.160	**0.730**	0.349	0.221
slike–Like	0.177	**0.559**	**0.510**	0.149
ngerous–Safe	-0.014	0.471	0.421	0.140
oomy–Cheerful	0.253	0.123	**0.720**	-0.045
pleasant–Pleasant	0.187	0.298	**0.718**	0.150
ld–Warm	0.219	0.336	**0.632**	0.175
comfortable–Comfortable	0.230	0.417	**0.523**	0.402
rce–Equable	-0.286	0.021	0.003	**0.763**
itating –Calm	0.151	0.262	0.288	**0.719**
nple–Complex	0.067	-0.199	-0.121	0.217
genvalue	10.293	2.425	1.607	1.066
m of squares adings after rotation)	5.101	4.389	3.324	2.066

The participant evaluated the adjective pairs described in Table1 in a five-point-scale rating using the SD method as impression valuations for factor analysis.

Table1 shows the commonality and factor loads of each item after a Varimax rotation and give the explanation rate of variance for each factor. Each factor was interpreted based on the whose absolute value of factor loading was 0.50 or more.

First, **factor 1** was made to be **hypersensitive** based on “sensitive,” “fast,” “clear” and so on. **Factor2** was based on **affinity**: “human,” “natural,” “friendly” and “accessible.” **Factor3** was made to be **comfortable** and was based on“cheerful,” “pleasant,” “warm” and so on. **Factor4** was made to **be quiet**:“calm” and “equable.” **Factor 5** was made to be **complex** :“complex.”

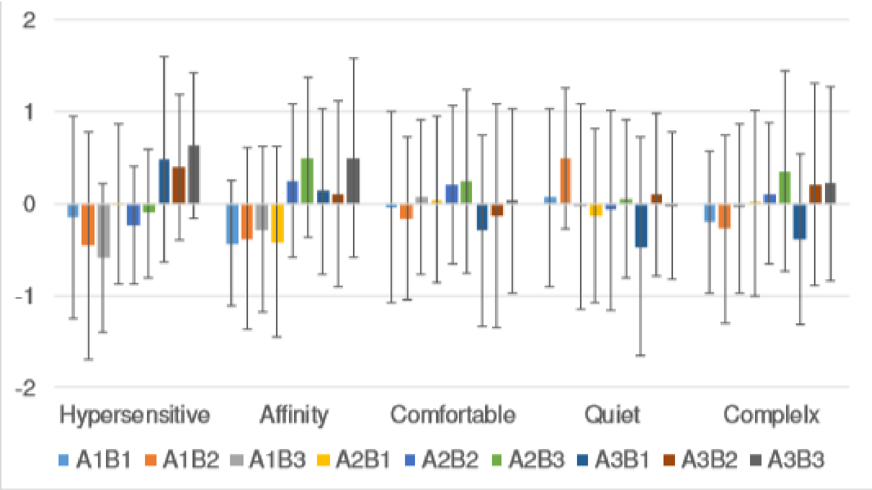

Figure 4: Factor scores for each condition

To compare the impression of each condition when encountering the tactile sense of grasping the robotic hand, the standard factor scores were calculated as an impression evaluation of gripping expressiveness.

Figure4 shows **the averages and standard deviations** of the standard factor scores by each conditions.

Here Table2 shows the **result of analysis of variance(ANOVA)** based on the standard factor scores.

Table 2: ANOVA result based on the standard factor scores

	A (gripping force)		B (holding duration)		AB interaction	
	f	p	f	p	f	p
Hypersensitive	17.820	**<0.001****	0.822	0.449	0.777	0.544
Affinity	8.808	**<0.001****	4.660	**0.017****	2.341	0.064+
Comfortable	2.150	0.133	1.075	0.353	0.320	0.864
Quiet	1.060	0.358	2.637	0.087+	0.996	0.417
Complex	1.402	0.261	2.906	0.069+	0.959	0.436

+: p<.1, *: p<.05, **: p<.01

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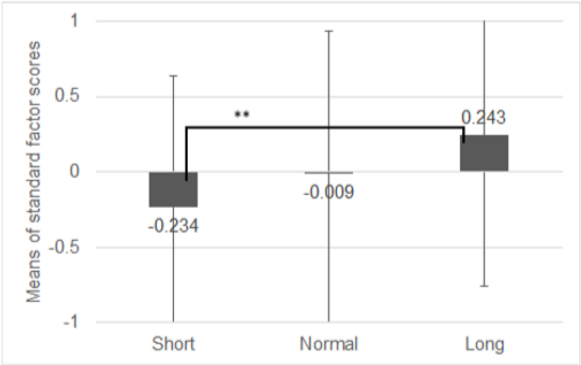

Figure 7: Significant difference in multiple comparisons of main effect for "affinity"

Conducted multiple comparisons of main effect among three levels of the factor A(Figure5). There were significant differences between the Strong level and other levels while the scores were gradually increased corresponding to the gripping force.

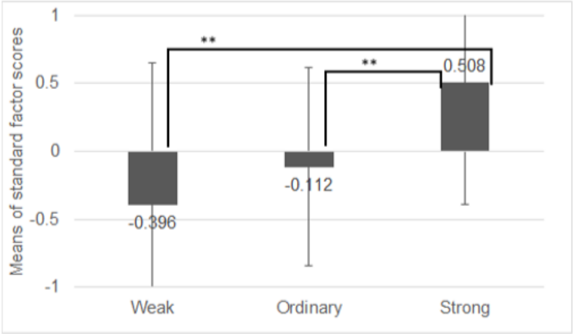

Figure 5: Significant difference in multiple comparisons of main effect for "hypersensitivity"

As shown in Figure6, there were significant differences between the Weak level and other levels while the scores were gradually increased corresponding to the gripping force.

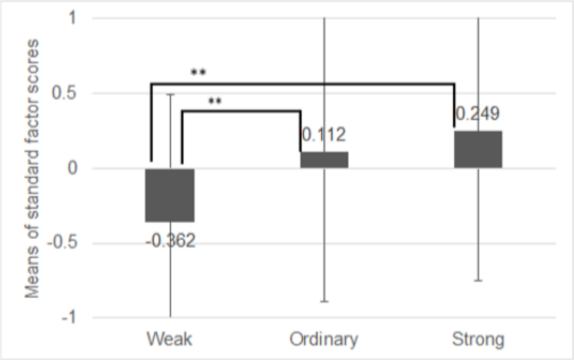

Figure 6: Significant difference in multiple comparisons of main effect for "affinity"

Figure 7 also showed a significant difference between the Short and Long levels, while the average score of the Normal level was about an intermediat evalue of the Short and Long levels.

Discussion

Further more, there were several significant differences by the gripping manners (strength and duration). The standard factor scores for the five extracted factors as impression of the robotic hand were processed by the two-factor ANOVA and the result showed significant differences of the hypersensitivity and affinity; the difference in gripping strength seemed to affect hypersensitivity and affinity and the difference in holding duration seemed to affect affinity.

It is conjectured that the score of hypersensitivity elevated by the stronger grip.

It is also presumed that the strength of the Strong conditions were perceived as human-like or natural grip. They should continue their verification on naturalness of the gripping manner to be positively accepted.

In regard to the gripping duration of the robotic hand, it was shown that the longer gripping duration made the users feel higher affinity.

The set of the holding duration in the experimental configuration had a limitation, so we should verify the effect of holding duration with a wider range of the levels in the experiment setting.

From the ANOVA for other three factors of the impression, there was no significant result.

These factors are still expected to be related to the elements of the gripping manner except the strength and duration, such as the gripping position and direction on the user's hand.

Discussion

Contents

- Abstract
- System Design
- Discussion
- **Conclusion**

Conclusion

In this study, it proposed a robotic hand to provide tactile interaction with users who have physical or psychological difficulty in daily life such as bedridden patients for lessening their loneliness and stabilizing their minds.

In this paper, they especially focused on the gripping manner of the robotic hand holding on the user’s hand as a physical contact. The effect of the expression of the robotic hand of the gripping manner based on based on the holding duration and gripping strength on the user’s impression was examined. As a result, five factors (hypersensitivity, affinity, comfortable, quiet, and complex) were extracted from the results of the factor analysis. In addition, the ANOVA results of the standard factor scores of the five factors showed that the hypersensitive and affinity increase as the gripping power strengthens, and that the longer holding duration increases affinity.

In the future, they consider that it is necessary to design the movement of the robotic hand combined to the physiological phenomenon on the skin to realize more realistic physical contact.

Thank you!

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趙　哲宇

”A Conversational Robotic Approach to Dementia Symptoms”

Ryuji Yamazaki, Hiroko Kase, Shuichi Nishio, Hiroshi Ishiguro

Hokkaido University
Intelligent Robot System Laboratory
Katsumasa Segawa

はじめに

研究背景

従来の研究から

介護スタッフの不足

⇨認知症患者の社会的交流の時間の減少 ⇨ **認知症の促進**

解決策

ソーシャルメディアを用いたコミュニケーション

社会的関係の創造により認知症を防止

はじめに

研究目的

ソーシャルメディアの問題点

認知症患者に用いるのは複雑，困難

新たな解決策…ロボットとの対話

直感的であり簡単

ロボットとの対話が認知症患者にどのような影響を与えるのか調査

実験概要

実験環境

実験内容

・オペレーターがロボットを通じて被験者と会話

・オペレーターは被験者から遮蔽

・対話時間…一日20分

・会話の内容は被験者の思い出
（学校の思い出，人生の出来事，家族etc…）

ロボットの影響を10週間にわたって計測

実験概要

被験者

被験者は認知症高齢者の女性5名

MMSE

・認知症重症度を測るための指標
・値が低いほど認知機能が低い（Ⅰ期…自立できる　Ⅱ～Ⅳ期…認知症）

Participant	Gender	Age	MMSE	Indepen-dence	Type of dementia
1	Female	94	0	IV	Dementia
2	Female	84	4	III	Alzheimer's
3	Female	84	7	IV	Lewy body
4	Female	84	10	IV	Alzheimer's
5	Female	93	15	III	Alzheimer's

実験概要

結果の尺度

NPI-NH…認知症患者の神経症状を評価

「妄想」,「幻覚」,「興奮」,「うつ」,「不安」,「高揚」,「無関心」,「脱抑制」
「過敏性」,「異常な運動行動」,「睡眠と夜間の行動障害」,「食欲」の12項目

各項目を重症度0～4点✖頻度0～3点の12点満点で評価

職業的破壊性尺度 …ケアスタッフの苦痛の尺度

各被験者のケアを行なっているスタッフ2名✖0～5点の10点満点で評価

各スコアを実験開始時，５週目，10週目に計測

解析手法

検定手法

フリードマン検定

・ノンパラメトリックな検定手法
・3群以上の他群の検定を行う
・正規分布に従ってなくとも使用可能
・順序尺度を尺度水準にとり検定を行う

有意水準$\alpha = 0.05$として$p \leq 0.05$であれば
有意差を示すこととする

実験結果

NPI-NHの項目の推移

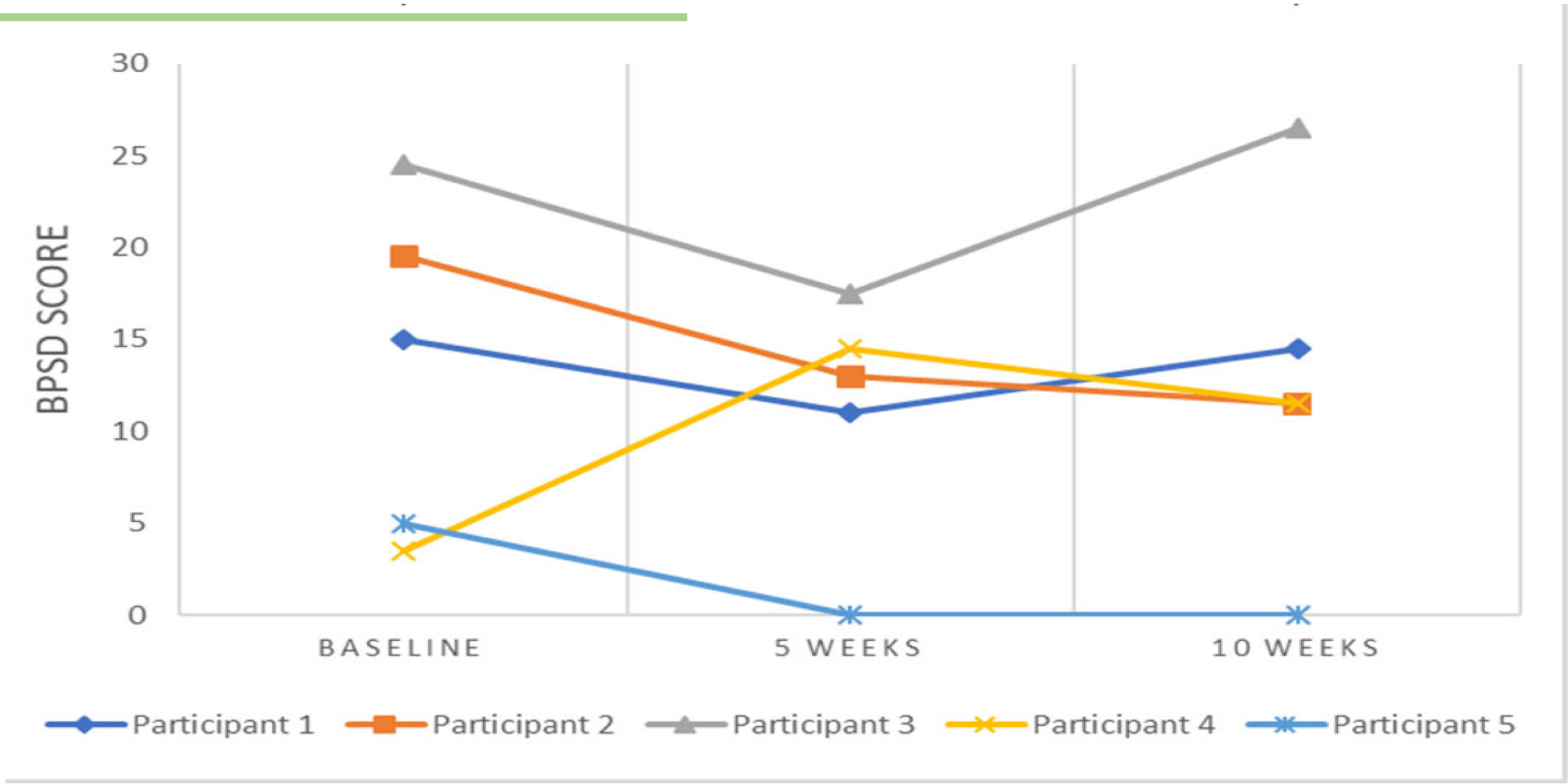
NPI-NHの各項目のスコアにおける統計量
各値はMean±SD

n=5	Baseline	5 weeks	10 weeks	P-value
Total score	1.1±1.7	0.9±1.6	1.0±1.7	0.190
Subscale score				
Delusions	1.8±1.5	1.8±1.6	2.0±1.7	0.368
Hallucinations	0.9±0.6	0.6±1.2	0.7±1.2	0.607
Agitation / Aggression	2.2±2.4	2.2±1.6	2.5±2.0	0.761
Depression / Dysphoria	0.9±1.2	0.1±0.2	0.1±0.2	0.717
Anxiety	0.5±0.4	0.1±0.2	0.1±0.2	0.050*
Elation/Euphoria	1.0±0.9	1.2±1.1	1.4±1.6	0.264
Apathy / Indifference	1.6±3.0	1.6±2.5	1.8±2.4	1.000
Disinhibition	1.4±0.9	1.2±1.1	1.7±1.4	0.368
Irritability / Lability	0.4±0.8	0.3±0.6	0.9±1.8	0.368
Aberrant motor behavior	1.5±2.3	2.3±2.6	1.9±2.6	0.867
Sleep and night-time behavior disorders	0.3±0.6	0.2±0.2	0.3±0.4	0.670
Appetite and eating change	1.2±1.0	0±0	0±0	0.050*

P値より「不安」「食欲」に関して有意差がある

実験結果

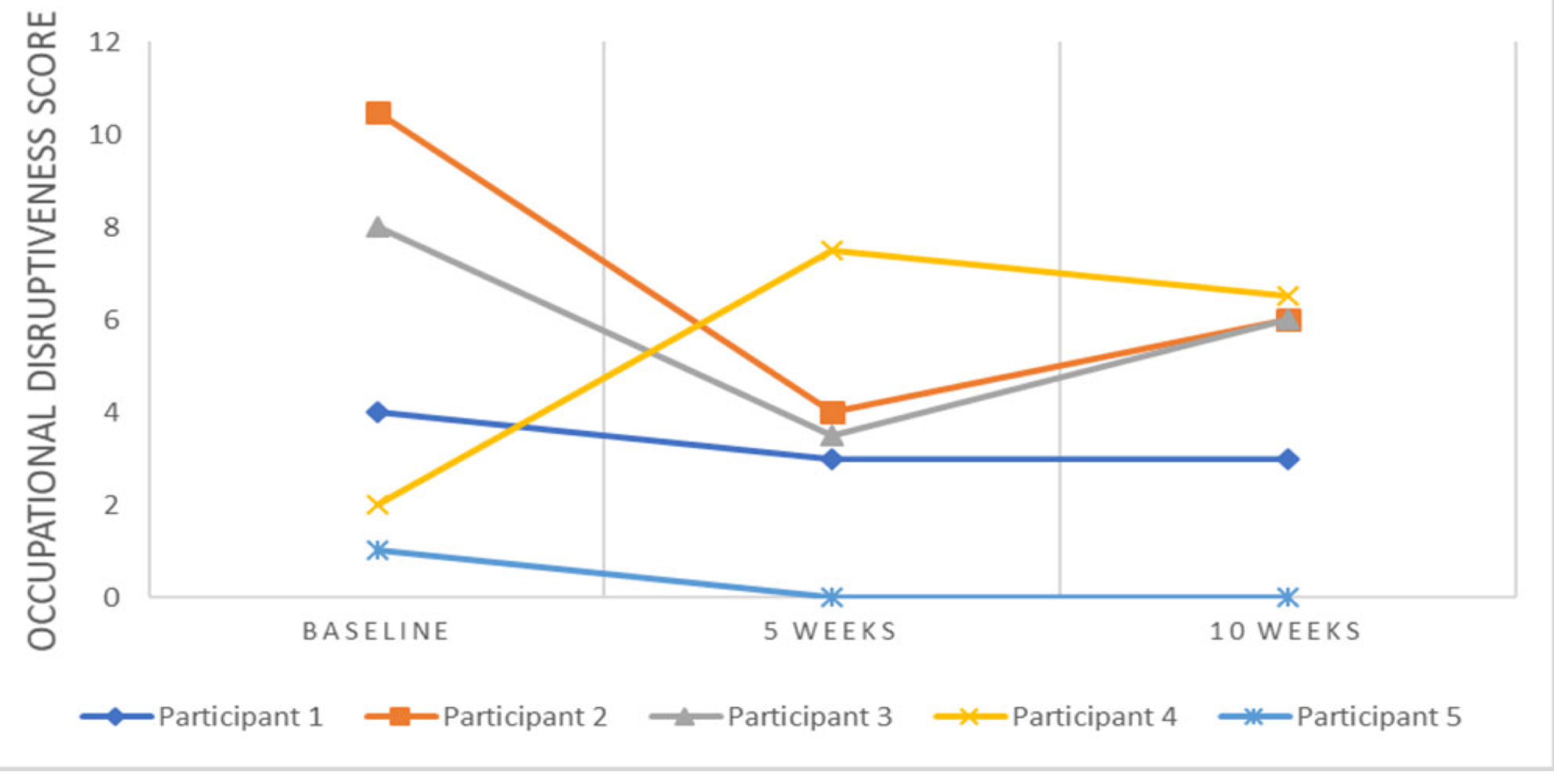
NPI-NH合計スコアの推移



被験者４を除く全員が5週目にスコアが減少
５週目から10週目に関してはスコアの減少が見られない

実験結果

職業的破壊性尺度の推移



NPI-NHと同様な推移
5週目から10週目に関してスコアの増加が見られる

おわりに

実験結果より

NPI-NHの項目において
「不安」「食欲」において有意差あり

NPI-NH，職業的破壊性尺度のスコアにおいて
５週目に減少傾向，10週目には増加している被験者もいる

問題点

・被験者が少ない
・会話の内容がパーソナライズされていない

より長い期間被験者の心を惹きつけるアプローチ法の開発

"Compact Real-time avoidance on a Humanoid Robot for Human-robot Interaction"

D. Nguyen, M. Hoffmann, A. Roncone, U. Pattacini, G. Metta,
HRI 2018

システム情報科学コース 知能ロボットシステム研究室
修士1年 鶴園 卓也 (46193192)

背景

既存のロボットは工場などで
決められたタスクを処理

今後

未知の環境でより自律的に動作
人間と空間を共有する

人間との衝突を避け安全な動作が求められる

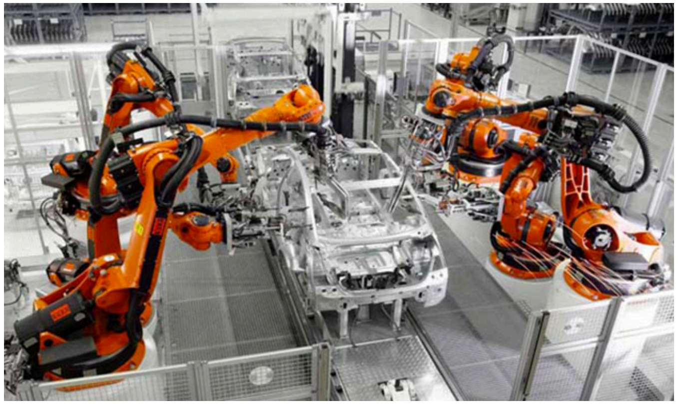


図　産業用ロボット[1]

図　二足歩行ロボット[2]

[1]産業用ロボットとは, https://www.sk-solution.co.jp/robotics/industrial_robot/
[2] ASIMOの歴史, https://www.honda.co.jp/ASIMO/history/asimo/index.html

目的

人間とロボットの物理的な相互作用
pHRI(physical human-robot interaction) を安全にする

実現するフレームワークの提案

周囲の人間の動きを把握し

- 目標動作を達成すること(グローバルな目標)
- 反応性障害物回避(ローカルな目標)

ヒューマノイドロボットiCubを対象にシステムを開発

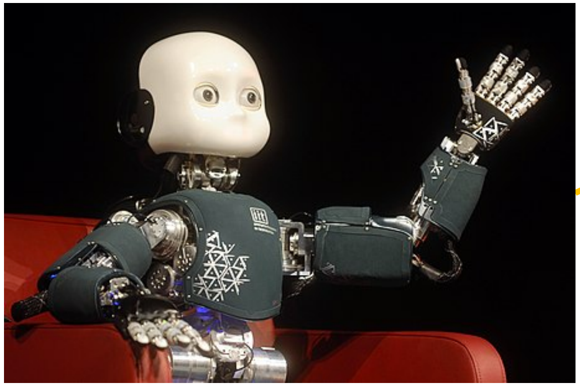


図　iCub[1]

オープンソースロボット
高さ 1[m], 重要 22 [kg]
3自由度の頭部
7自由度の腕 (接触センサ)
ステレオカメラ(頭部)

[1] iCub, https://en.wikipedia.org/wiki/ICub

提案手法

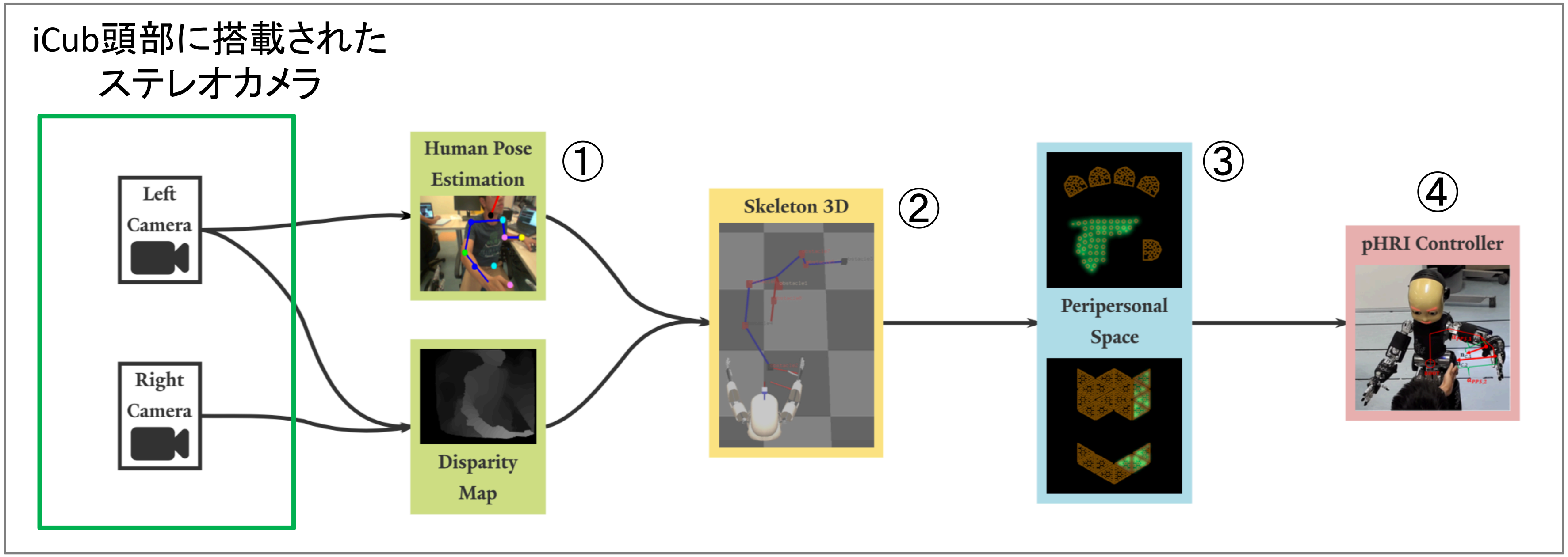


図　システムの概要

①人間の姿勢推定
　左カメラを用いて人間の姿勢推定

②姿勢情報の3次元変換
　左右のカメラを用いて深度を計測

③身体近傍空間PPSによる衝突判定
　ロボットと人間の接触危険性を判定

④制御
　トリガが発生した場合，回避動作

姿勢推定

DeeperCut [1]

画像から複数人の姿勢を同時に推定

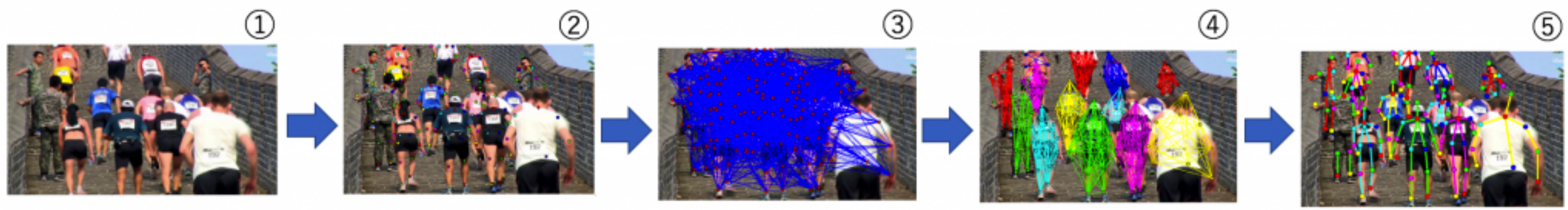


図　動作の概要

① カラー画像の入力
② CNN型のモデルを用いて，キーポイント(肘や顔などの人物の部位) を抽出
③ キーポイント同士の全ての繋がりを組み合わせ
④ 人物の組み合わせを抽出
⑤ キーポイントの代表部分を出力

キーポイントをロボットが回避する障害物として設定

[1] EldarInsafutdinov,LeonidPishchulin,BjoernAndres,MykhayloAndriluka,and Bernt Schiele. 2016. Deepercut: A deeper, stronger, and faster multi-person pose estimation model. In European Conference on Computer Vision. Springer, 34–50.

姿勢情報の3次元変換

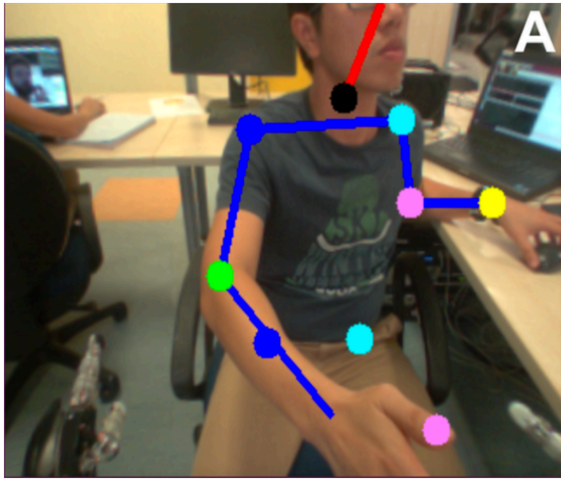


図　DeeperCutによる姿勢推定

図　ステレオ視による深度画像

生体力学的制約を適用

近傍7×7ピクセルの3D位置を平均

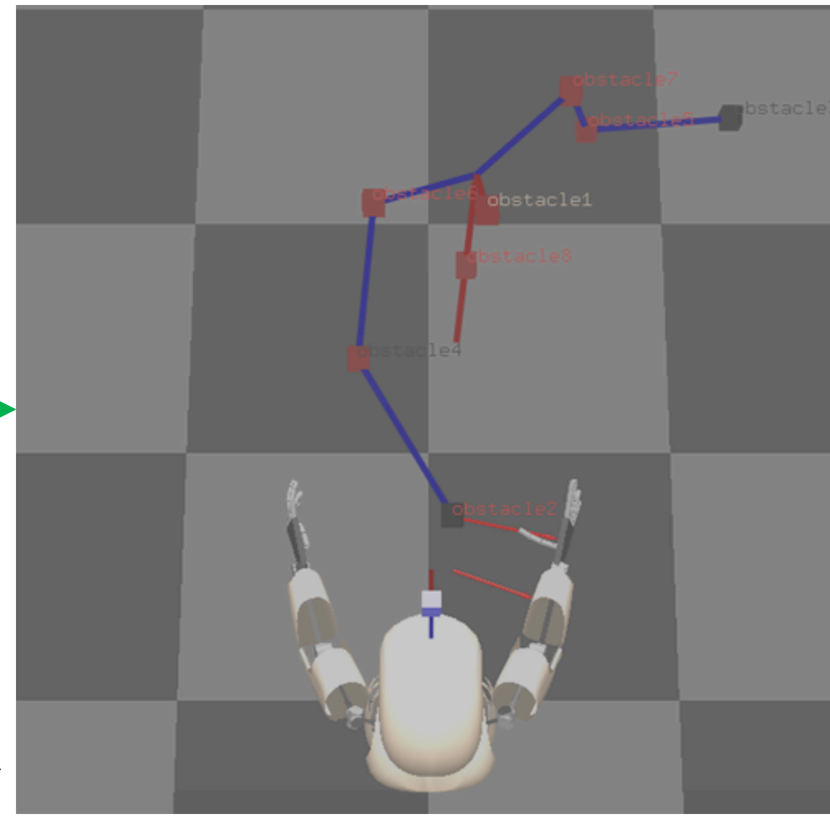


図　推定された3次元姿勢

身体近傍空間PPS[1]による障害物回避

生物学を基に提案された手法．受容野RF (receptive field) に存在する障害物に対して衝突するかどうか，どれだけ危険かどうかを視覚的に把握する

手のひら : 5個のRF
腕 : 24個のRF

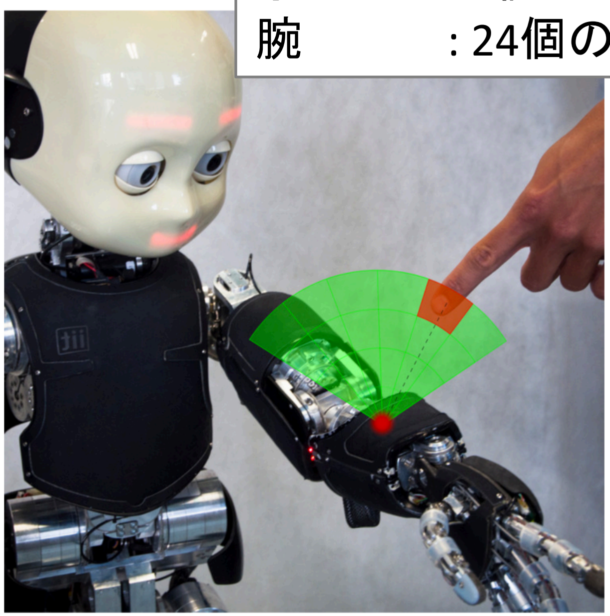


図　RFの概要

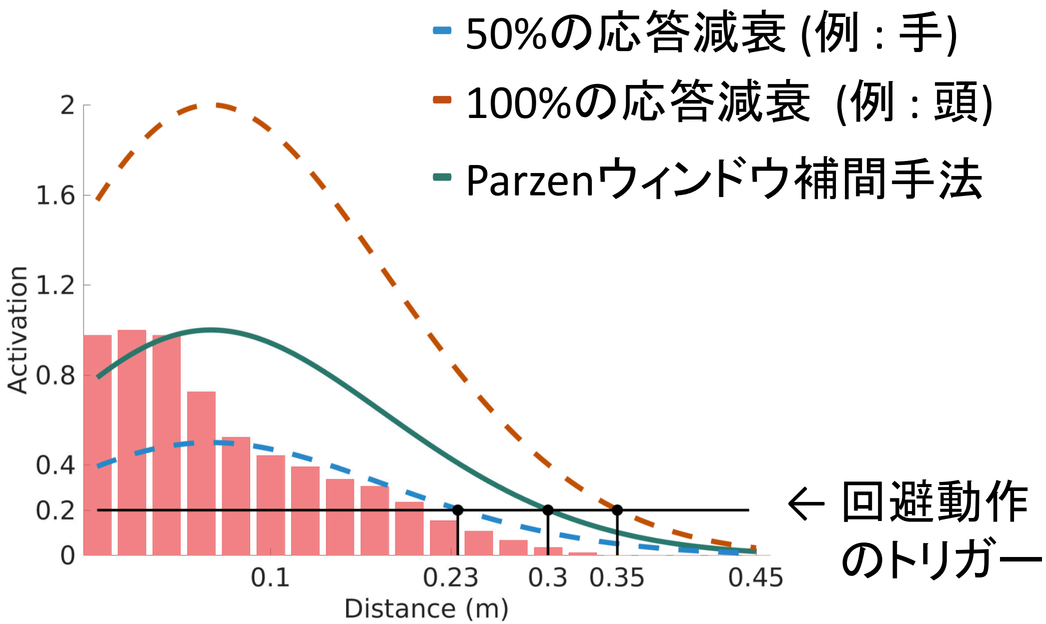


図　距離と活性化の関係

[1]A. Roncone, M. Hoffmann, U. Pattacini, and G. Metta. 2015. Learning periper- sonal space representation through artificial skin for avoidance and reaching with whole body surface. In Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on. 3366–3373.

実験1

静止状態での回避動作

動画　静止状態での回避動作

実験2

円軌道を描いた状態での回避動作

動画　円軌道を描いた状態での回避動作

実験3

頭部の回避動作

動画　頭部の回避動作

まとめ

- 人間の行動を把握し，衝突を回避するフレームワークの開発を行った.
- 実験により，動作途中に人間の介入があった場合でも安全に回避することができた.

課題

1. 事前衝突のみを考慮している

   衝突した場合の動作を実装していないため，接触センサなどを用いて安全に停止するなどの工夫が必要

2. 速度を利用していない

   提案手法は、静的な位置状態で回避動作
   対象物やロボットアームの速度を考慮することで，より柔軟な回避行動を実現できる

Effects of Capability and Context on Indirect Speech Act Use in Task-Based Human-Robot Dialogue

Kazuma Tateiri

Introduction

- Humans often use “indirect speech acts” (ISAs) to other humans.
- For example, “Could you open the door?” is a ISA.
- This sentence is literally questionnaire.
- But the actual intention of this speech is request to open the door.
- ISAs are used to achieve socio-cultural goals (e.g. politeness).
- The use of ISAs differs individually and cross-culturally.
- But their use is generally accepted feature of natural human dialogue.

Motivations of this research

- The authors suspect that not handling ISAs might be one of the largest stumbling blocks preventing successful natural language-based human-robot interaction outside of the laboratory.
- Only recently have word error rates on speech recognition fallen into the single digits (6.9%), and yet this rate is considered to be too high.
- But if ISA use rates is considerably higher than 6.9% in human-robot dialogues, it deserves more attention from the research community.
- It is important to investigate the extent to which ISAs will be used.

The seven hypotheses they created:

1. ISAs are central to task-based human-robot dialogue regardless of task context. ISAs will be used with sufficient frequency that not handling them would yield an unacceptably high utterance error rate greater than or equal to the current word error rate of 6.9%.
2. This high frequency of ISA use will occur in both conventionalized and unconventionalized task contexts.
3. Human social conventions will carry over into human-robot interactions.
4. ISAs will be more often used in conventionalized scenarios.

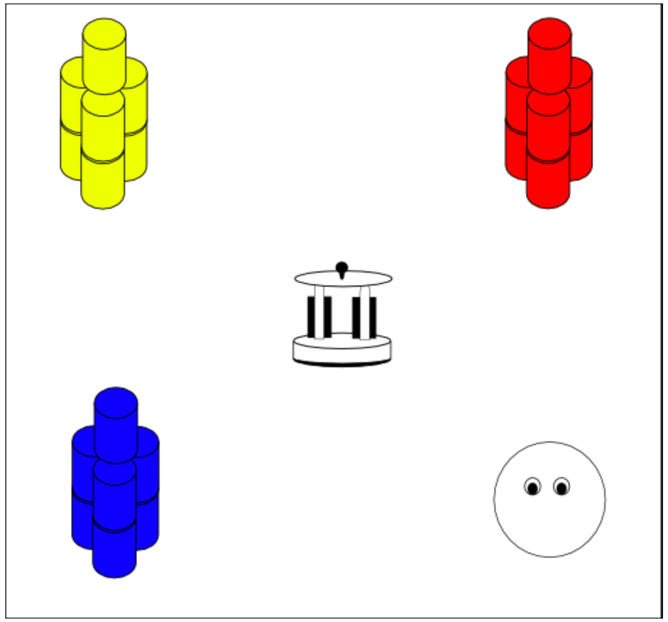
The seven hypotheses they created: (2)

5. Even if a robot demonstrates itself to be fundamentally incapable of understanding ISAs, humans will prefer to continue using ISAs rather than direct commands.
6. If the hypothesis 1 holds, a human interacting with a robot unable to understand ISAs should be less efficient in accomplishing a task than a human interacting with a robot able to understand ISAs.
7. If the hypothesis 1 holds, a robot unable to understand ISAs should be perceived less favorably than a robot able to understand ISAs.

Methodology

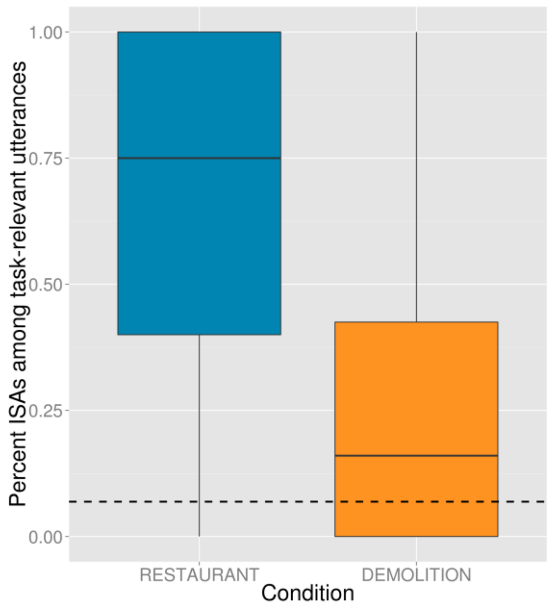
- They conducted a Wizard-of-Oz between-subjects experiment.
- It employed two scenarios: *restaurant* and *demolition*.
- In the *restaurant* scenario, the participants were provided with a list of three “courses” which they could request to be delivered.
- In the *demolition* (解体) scenario, the participants were provided with a list of three towers which they could request to be knocked down.
- Each scenario had two conditions: *understood* and *misunderstood*.
- Each participant was randomly assigned to one of four conditions:
    - Such as (*restaurant*, *understood*), (*demolition*, *misunderstood*), etc.

Room setups



- In the *restaurant* scenario, the room was empty.
- In the *demolition* scenario, the room contained three colored towers of aluminum cans, as shown in figure on the left:

Behavioral results



- The majority of participants (69%) used at least one ISA.
- 46% of task-relevant utterances were coded as ISAs.
- ISAs were much more frequently used in the *restaurant* condition (0.75 ± 0.39) than in the *demolition* condition (0.16 ± 0.34). (left figure)
- ISA use rates was far above their threshold (6.9%) in both the *understood* (1.0 ± 0.49) and *misunderstood* (0.4 ± 0.27) conditions.

Implications

- The first hypothesis (H1) was that ISAs would be consistently used, even after repeated demonstration of an inability to understand them. As seen in the results section, ISAs were used by the majority of participants and constituted the majority of task-relevant utterances.
- The second hypothesis (H2) was that this high frequency of ISA use would occur across both conventionalized and unconventionalized task contexts. While ISAs were observed in both conditions, ISAs were used far less frequently in our unconventionalized task context, at a rate which did not clearly support this hypothesis.

Implications (3)

- The results suggest a significant need for robots engaging in task-based human-robot dialogue interactions to be able to understand ISAs.
- Specifically, the results suggest that failing to understand ISAs could result in an expected utterance error rate as high as 46% (the mean frequency of ISAs among task relevant utterances) – a number that is clearly unacceptably high for task-based interactions.

Understanding Affective Experiences With Conversational Agents

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Background

- There are a lot of researches about technologies of Conversational Agents.
  - voice interface and the dialogue system
  - human-like interaction
  - intelligence

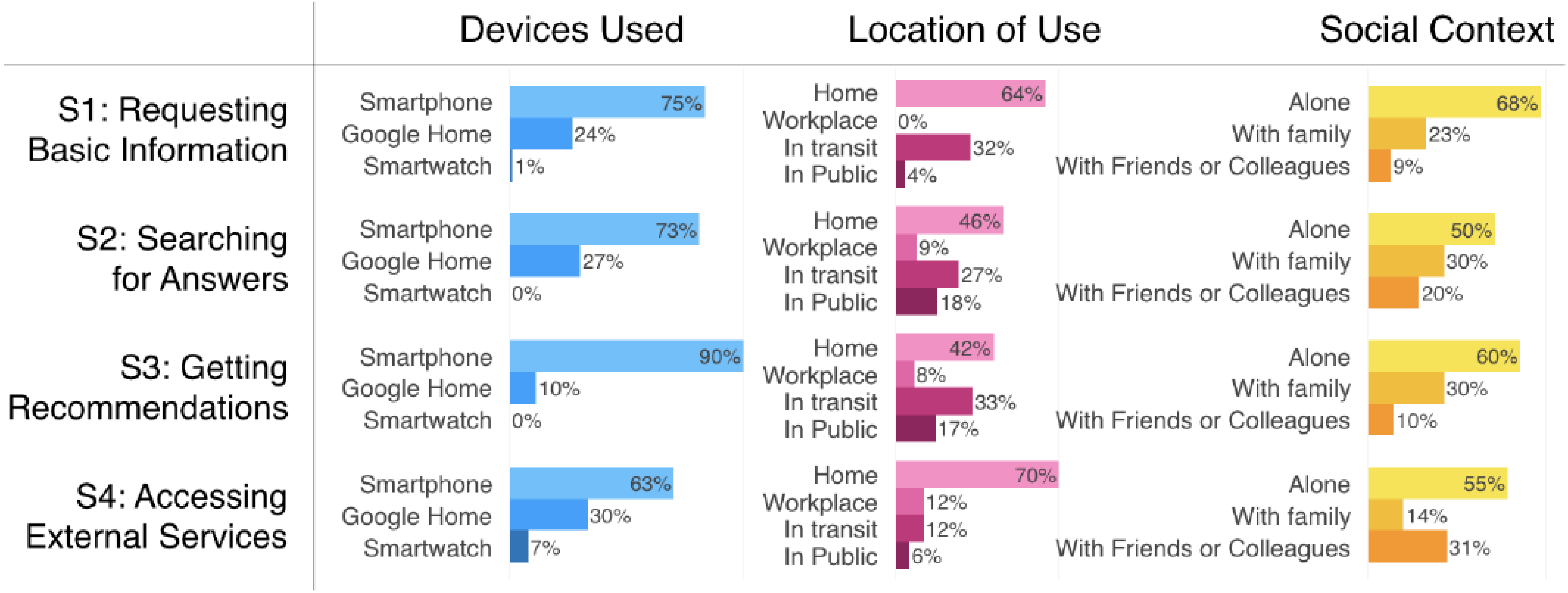
- Understanding Affective Experiences for better interaction experience.

Implementation

- Survey research about experience on Google Assistant
  - Critical incident method, which requires users to report an experience that they have had for reliability of survey.

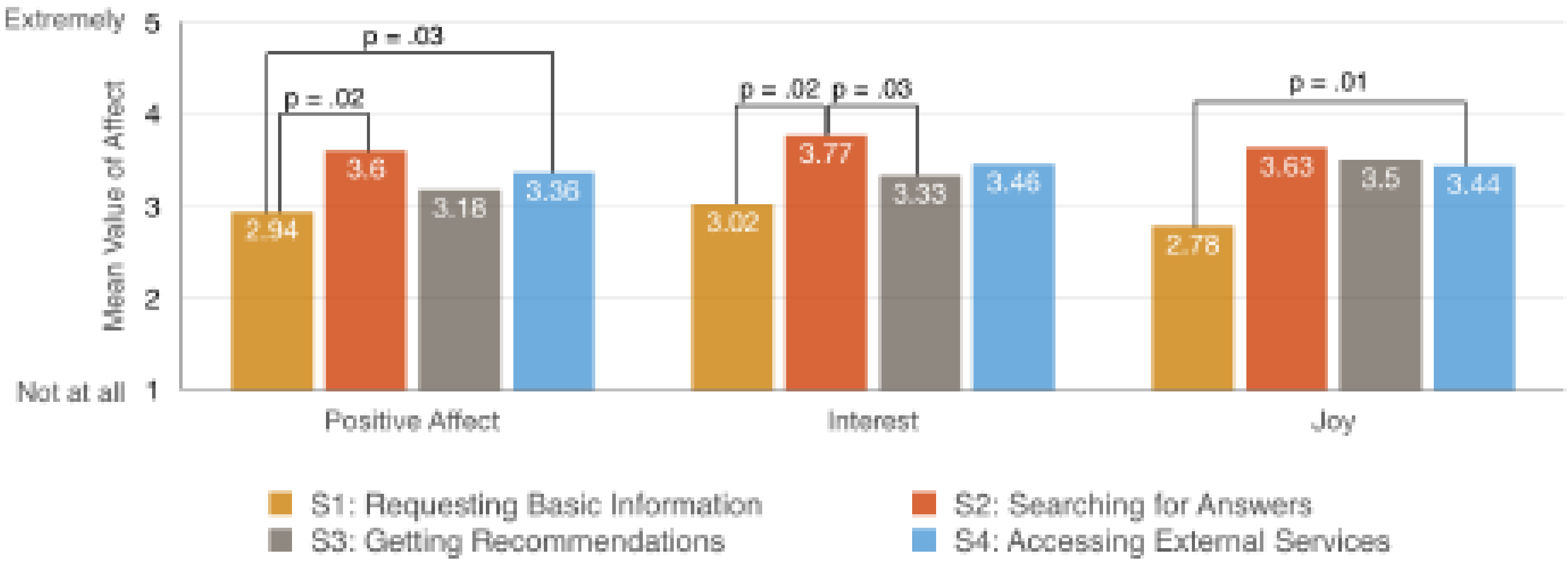
- mathematical analysis
  - PCA
  - Correlation analysis

Experiment



- Random context and scenarios for better reliability of survey on 171 participants

Affective Responses in the Four Scenarios



- They found that users' overall experience was positive with interest being the most salient positive emotion. And affective responses differed depending on the scenarios.

interpretation of correlation

Table 3: Correlation Between Product Qualities and Affect

Product Quality	Positive Affect	Negative Affect
Hedonic	.47 *	-.07
Pragmatic	.32 *	-.42 *
Attraction	.28 *	-.35 *

* $p < .001$

- In positive affect, the hedonic quality was higher than that of the pragmatic quality.
- Pragmatic quality was found to significantly influence negative affect.

Summary

- Contribution: help designers better understand users' expectations across different scenarios and contexts, and therefore design for a positive user experience.

- Limitation: recalled memories may be inconsistent with interactions observed in process.

Second Language Tutoring using Social Robots: A Large-Scale Study

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Mirjam de Haas (Tilburg University), Laura Hoffmann (Bielefeld University),
Junko Kanero, Ezgi Mamus (Koç University), Jean-Marc Montanier (SoftBank Robotics Europe),
Cansu Oranç (Koç University), Ora Oudgenoeg-Paz (Utrecht University),

outline

- course of 7 lessons designed to help children learn English as a foreign language using a social robot

- multi-staged experiment conducted to measure the effectiveness of a social robot in teaching children:

➡ comparing the effect of learning from a robot tutor accompanied by a tablet vs learning from a tablet application alone

experiment; overview

- pre-test (checking if target vocabulary of 34 words is already known)
- 7 lessons series (with 3 differnt settings)
- post-tests (immediate and delayed)

participants

- 194 children (5-6 years old, Dutch native speakers)

Condition	N	Gender N_b/N_g	Avg Age + SD (Y;M)	(M)
Iconic gestures	54	31/23	5;8	5
No iconic gestures	54	28/26	5;8	5
Tablet-only	54	24/30	5;9	5
Control	32	14/18	5;7	5

target vocabulary

L	Setting	Target words
1	Zoo	one, two, three, add, more, most
2	Bakery	four, five, take away, fewer, fewest
3	Zoo	big, small, heavy, light, high, low
4	Fruit shop	on, above, below, next to, falling
5	Forest	in front of, behind, walking, running, jumping, flying
6	Playground	left, right, catching, throwing, sliding, climbing
7	Picture book	*all target words*

lessons; environmental setup

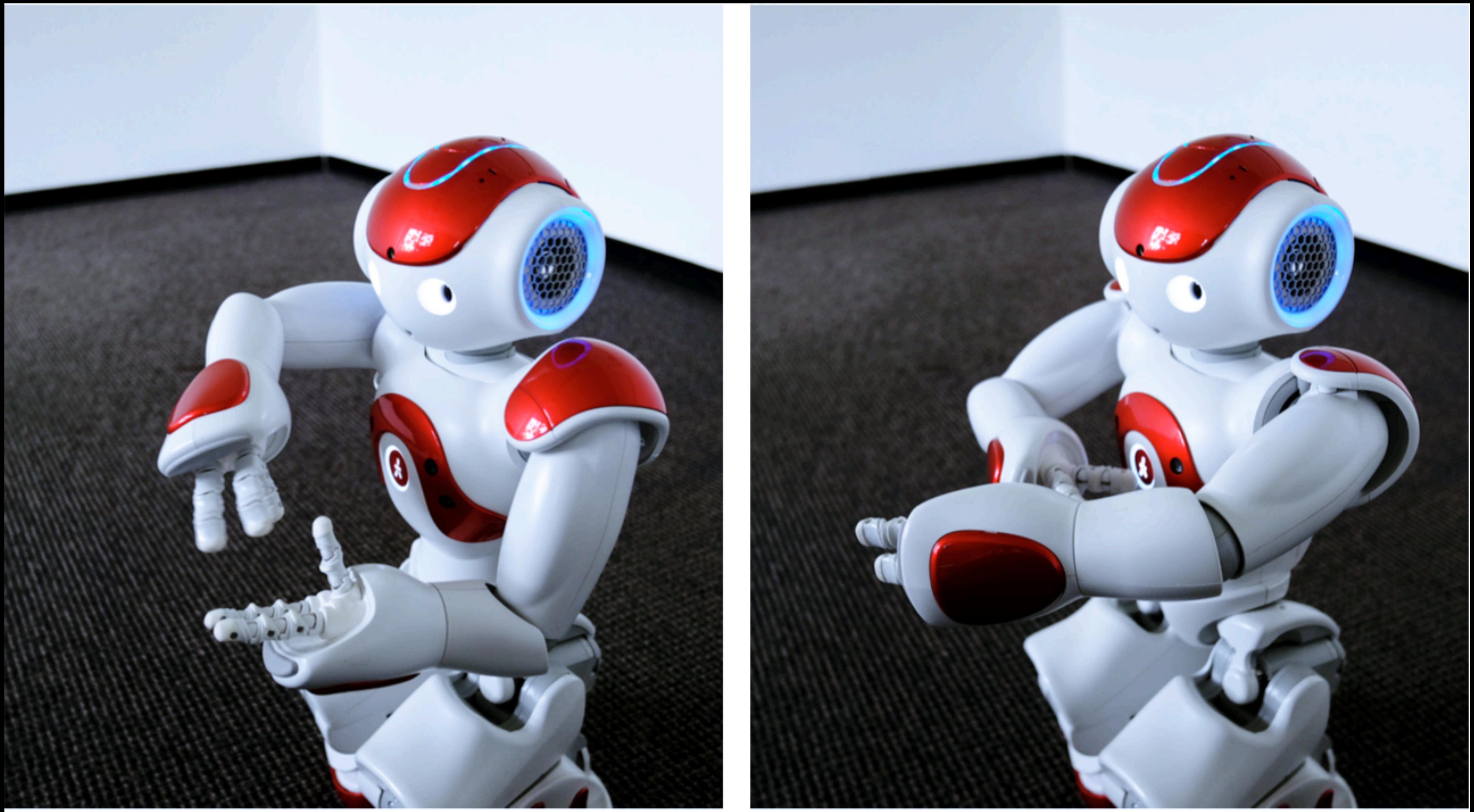
lessons; plan

1) introduction where the robot would greet the child by name, and present the new virtual environment (e.g. forest) that set the context of the lesson

2) words presentation and teaching/learning:
- robot's narration (e.g. "Look, elephants!")
- robot's verbal feedback (e.g. "Good job!", "Nice try, but you need to touch the monkey in the cage, try again!")
- robot's gestural feedback (in 1 out of 4 conditions)
- tasks for children within tablet-based game (e.g. release the monkey from the cage)

3) short test in which knowledge of each target word was tested twice in a random order (no feedback from robot during this stage)

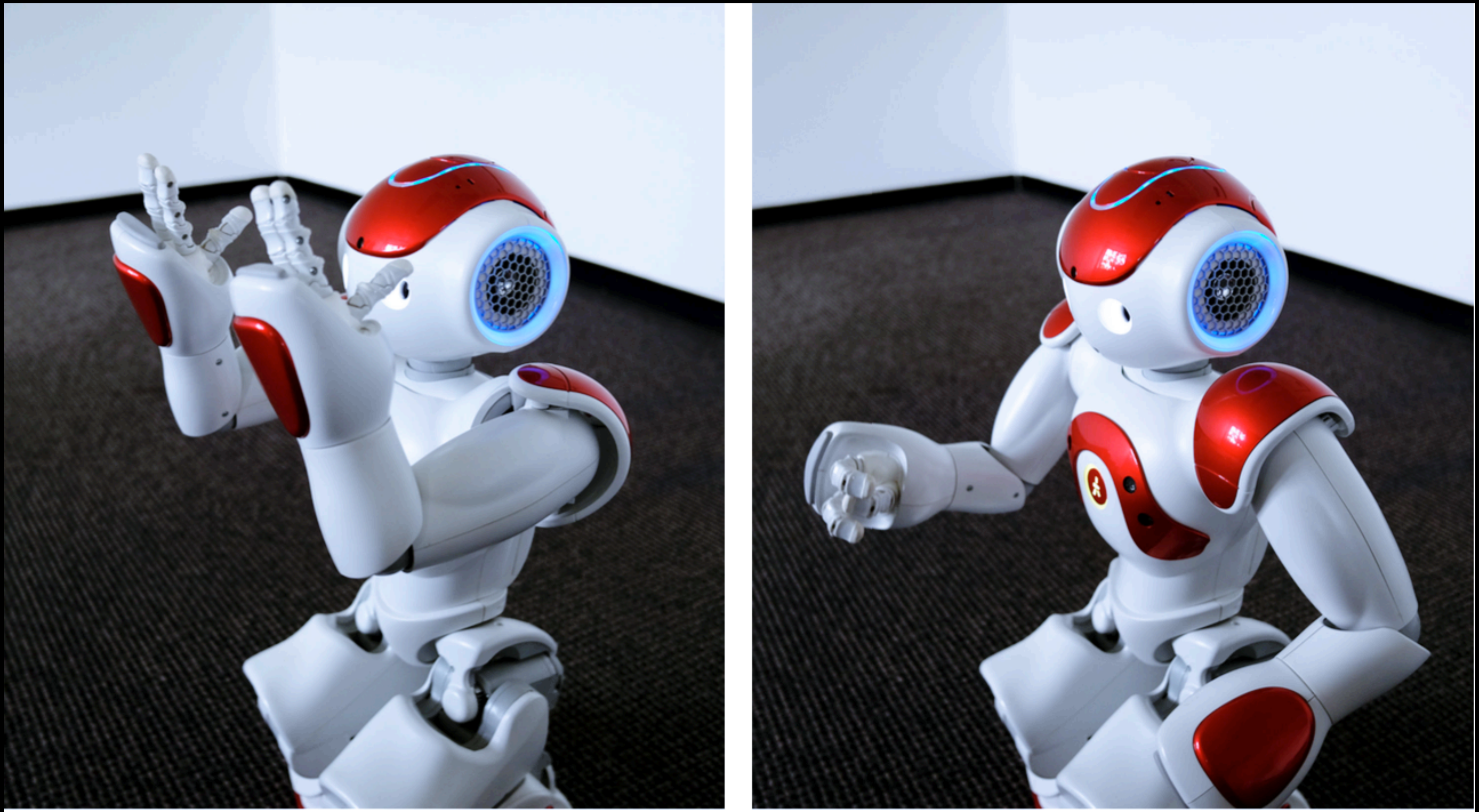
gestures; examples



(a) Add

(b) Behind

gestures; examples#2



(c) Four (d) Running

conditions

1) robot with iconic gestures + tablet

2) robot without iconic gestures + tablet

3) tablet-only without the robot

4) control condition where children danced with the robot but were not exposed to the educational material

post-experimential tests

- immediate post-test (max. 2 days after the final lesson)
- delayed post-test, (between 2 and 4 weeks after the final lesson; M = 2 weeks 5 days, SD = 2.70 days)

1) translation from English to Dutch
2) translation from Dutch to English
3) comprehension test of English target words

results

Condition / Test	Pre-test	Imm. post-test	Delayed post-test
Iconic gestures			
Trans(En-Du)	3.31 (3.09)	7.41 (5.17)	8.10 (5.06)
Trans(Du-En)		6.00 (4.23)	6.45 (4.62)
Comprehension		29.47 (5.85)	30.43 (6.22)
No iconic gestures			
Trans(En-Du)	3.47 (3.19)	7.69 (4.92)	7.88 (4.79)
Trans(Du-En)		6.43 (4.20)	6.43 (4.65)
Comprehension		29.39 (6.08)	29.75 (6.44)
Tablet-only			
Trans(En-Du)	4.04 (2.76)	7.96 (4.63)	8.63 (4.62)
Trans(Du-En)		6.57 (4.01)	6.67 (4.20)
Comprehension		29.73 (6.27)	30.25 (6.58)
Control			
Trans(En-Du)	2.48 (2.25)	3.48 (2.75)	3.97 (2.82)
Trans(Du-En)		3.07 (2.27)	3.52 (2.17)
Comprehension		24.31 (6.25)	25.62 (5.34)

Note: All scores indicate the average number of words correctly translated or comprehended (standard deviation within brackets). Minimum scores are 0, maximum scores are 34 for translation and 54 for comprehension. For comprehension, chance level is 18.

conclusions

- children in the experimental conditions scored higher than children in the control condition on all tasks
- no significant differences between groups with different conditions:

➡ children learn equally well from the robot and the tablet as from just the tablet

➡ children learn equally well from a robot producing iconic gestures and from one that does not produce such gestures

- scores of the delayed post-test were significantly higher than those of the immediate post-test

considerations & future work

- tablet's presence in conditions #1 & #2 may have limited the importance of the interaction between child and robot
- in condition #3 children could focus their attention solely on the tablet game; in 1# & #2 attention had to be divided between the two devices (robot & tablet)

➡ future trial without tablet

- gestures might have been ambiguous

➡ gestures redesign

- learning sessions with robots might have been too long

➡ getting rid of potentially redundant comments

YouTube video-presentation

https://www.youtube.com/watch?v=IS8CbzJZX4k

thank you
for your attention.

What is Human-like?: Decomposing Robots’ Human-like Appearance Using the Anthropomorphic roBOT (ABOT) Database

情報科学院メディアネットワークコース
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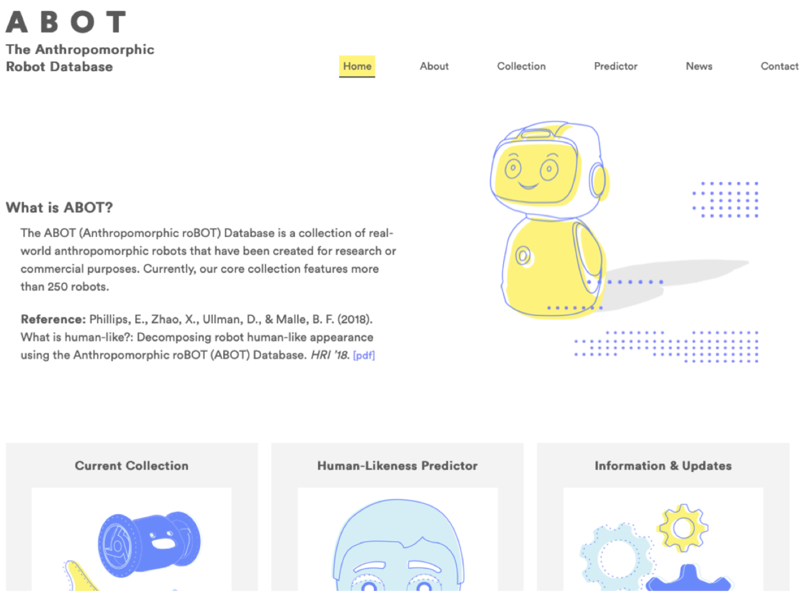
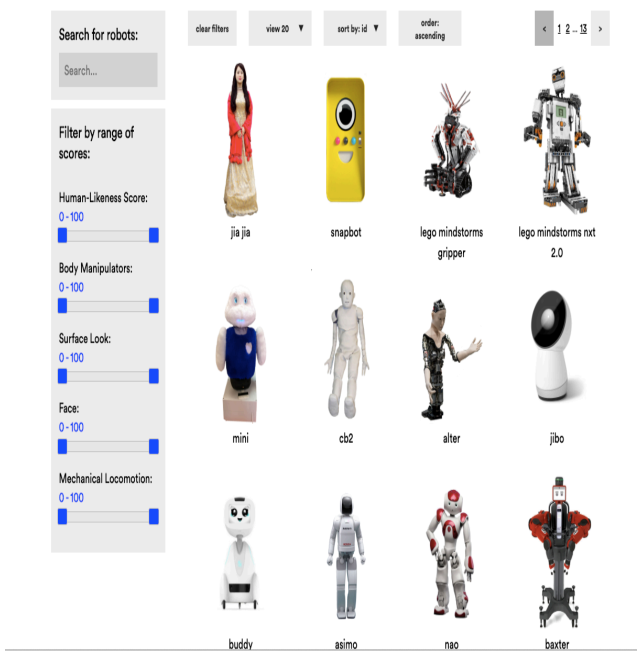




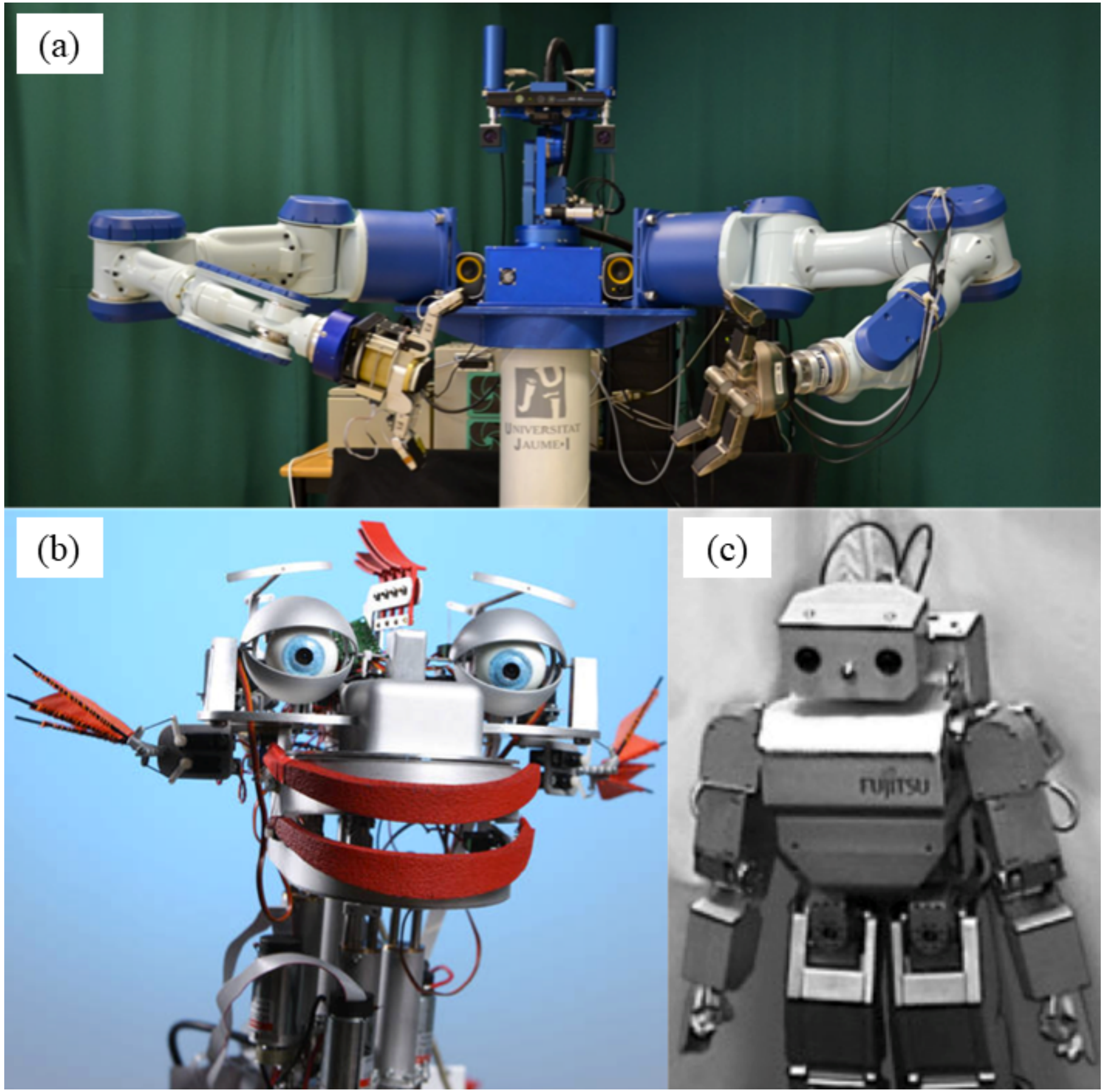
http://www.abotdatabase.info/collection

Background

- The appearance of a robot can have a significant impact on people's perception of intelligence, sociability, favorability, reliability, and compliance.
- Researchers warn about certain risks related to the human-like appearance of robots.
- It is necessary to deepen the systematic understanding of robots that look like humans.

Figure 1: Robots characterized as “humanoid” in (a) Stenzel et al. , (b) Wiese et al. , and (c) Meltzoff et al. .

Robots that share the same label across different studies may actually differ dramatically in their degree of human-likeness.



ABOT(Anthropomorphic roBOT)

- The largest repository of robots with human-like features to date.
- Identify distinct dimensions of robot appearance.
- Report two empirical studies
- Offer the Human-Likeness Estimator—a web-based linear equation.

269 images

gathering that varied in both number and type of human-like appearance features

200 images

Careful review of images

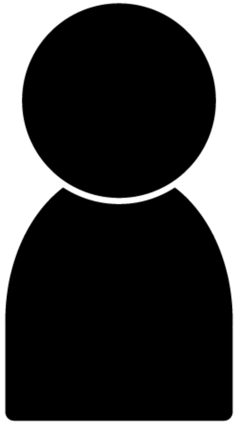
200 images

Image Selection and Editing

Study1 Investigate the appearance of the robot

via Amazon’s Mechanical Turk crowdsourcing website (mTurk).

採用人数	**1132人（man:501,women:619 不明:12）**
年齢	18歳から81歳（M = 36.07、SD = 11.68、4人未報告）
報酬	$0.5



Yes or NO ?

66 images

N = 1,140 (15 raters x 19 features x 4 blocks of robots).

- **Definition for each feature**

Feature:	Definition
Apparel:	Materials worn temporarily to cover the body.
Arm:	Upper limb typically used for manipulating objects.
Eye:	A round or oval shaped form that often gathers visual information.
Eyebrow:	A line above the eye usually consisting of hair.

Study1 Result

- The PCA in Study 1 yielded four appearance dimensions (i.e., feature bundles) .
- The “subscale scores,” (the bold-faced items in Table 2).
- (1) Surface Look,
  (2) Body-Manipulators,
  (3) Facial Features,
  (4) Mechanical Locomotion.

Together, these four dimensions accounted for three-fourths of the total variance among the 18 individual features.

Table 2: Principal Components Loading Matrix, Study 1.

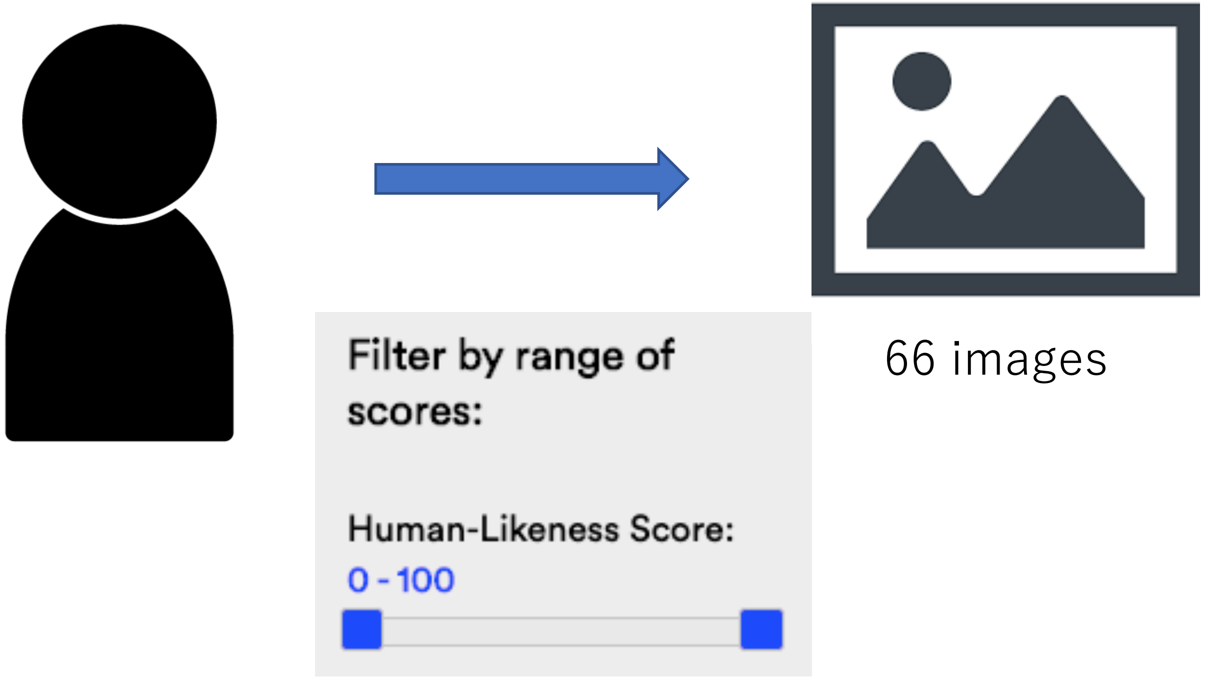
Feature	PC 1 Surface	PC 2 Body	PC 3 Facial	PC 4 Mech.
1. Eyelashes	**.88**	-.08	.15	-.04
2. Headhair	**.85**	.05	.03	-.06
3. Skin	**.83**	.07	.07	-.13
4. Genderedness	**.80**	.28	.17	-.12
5. Nose	**.71**	.05	.33	-.05
6. Eyebrows	**.69**	-.19	.38	.02
7. Apparel	**.68**	.28	.07	-.13
8. Hands	.12	**.93**	.06	.02
9. Arms	.02	**.92**	.10	.01
10. Torso	.07	**.90**	.19	.07
11. Fingers	.14	**.86**	.02	.05
12. Legs	-.06	**.74**	-.08	-.23
13. Face	.28	.14	**.90**	.02
14. Eyes	.14	-.02	**.88**	-.01
15. Head	.13	.49	**.73**	.03
16. Mouth	.48	.05	**.57**	-.07
17. Wheels	-.13	-.09	.01	**.92**
18. Treads/Tracks	-.18	.06	-.01	**.91**
Eigenvalue	4.67	4.30	2.81	1.79
% Variance	25.93	23.88	15.62	9.93
Subscale Cronbach's α	[illegible]9	.93	.83	.82

Note: **PC 1**: Surface Look, **PC 2**: Body-Manipulators, **PC 3**: Facial Features, **PC 4**: Mechanical Locomotion. Subscales derived from features with loadings in bold.

Study2 PREDICTING PHYSICAL HUMAN-LIKENESS

- Identified which appearance dimensions best characterize general human-likeness impressions.

participants	**100 (males:48,females: 50, lost:2)**
ages ranging	19 to 64 （M = 33.42, SD = 9.75 ）
報酬	$1.00



25 judges to each robot in each block and thus predetermined a total sample of N = 100.

Study2 Result

1. These average human-likeness scores across all the robots in our database ranged from 1.44 to 96.46, with M = 33.26, SD = 18.97.
2. A regression model using all 18 features explained 88.8% of the total variance of overall human-like scores (R = .94, F (18, 179) = 78.5, p <.001).

torso	**r_(semi－partial) = .31**
genderedness	r_sp = .44
skin	r_sp = .23
These three	78.4% of the total r_sp

2. A stepwise forward regression analysis with the 18 features as predictors.

Study2 Result

3 Predicting physical human-likeness from appearance dimensions.

Four regression-based principal component scores as predictor variables.

This model explained 82.5% of the variance in human-likeness, F (4, 193) = 227.0, p < .001.

Surface Look (37.2%)	**r_sp = .61**
Body-Manipulators (36.0%)	r_sp = .60
Facial Features (5.7%)	r_sp = .24
Mechanical Locomotion (3.6%)	r_sp = -.19

four subscale scores as predictors. This model explained 81.5% of the variance in human-likeness, F (4, 193) = 212.4, p < .001.

Body-Manipulators (28%)	**r_sp = .53 p < .001**
Surface Look (19%)	r_sp = .44 p < .001
Mechanical Locomotion (1.7%)	r_sp = -.13 p < .001
Facial Features (0.5%)	r_sp = .07, p = .025

Conclusion & Future work

- A more systematic, generalizable and reproducible study on the anthropomorphic appearance of robots and their impact on human-robot interaction.

- Robot integration into the ABOT database is constrained by both knowledge of existing robots and search procedures.
- The number and type of features need to be refined.
- How the robot's static appearance features interact with dynamic properties.