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Robotic Speech Synthesis: Perspectives on Interactions, Scenarios, and Ethics

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ABSTRACT
In recent years, many works have investigated the feasibility of conversational robots for performing specific tasks, such as healthcare and interview. Along with this development comes a practical issue: how should we synthesize robotic voices to meet the needs of different situations? In this paper, we discuss this issue from three perspectives: 1) the difficulties of synthesizing non-verbal and interaction-oriented speech signals, particularly backchannels; 2) the scenario classification for robotic voice synthesis; 3) the ethical issues regarding the design of robot voice for its emotion and identity. We present the findings of relevant literature and our prior work, trying to bring the attention of human-robot interaction researchers to design better conversational robots in the future.

CCS CONCEPTS
• Human-centered computing → HCI design and evaluation methods; • Computing methodologies → Artificial intelligence.

KEYWORDS
robot identity, emotion, speech synthesis, prosody, AI ethics

1 INTRODUCTION
The rapid development of speech synthesis in recent years has made it possible for computers to generate speech that closely resembles human speech, including emotional voice [20, 32]. Robotics is one of the applications that benefit most from this technology. Since the facial expressions and body movements of robots are currently difficult to make as natural as those of human beings, changes in the voice are the most common way to adapt to different scenarios [3, 34]. In this paper, we first illustrate the importance of prosody to emotional speech synthesis and the difficulty of synthesizing interactional aspects of speech. Through our prior work, we discuss the prosodic and emotional aspects of backchannels, as it is an important component of spoken dialogue that has been widely studied in human-robot conversation [1, 15, 29]. Next, we present our designed scenario classification for robotic speech synthesis and how people perceive robot voices in different scenarios. Finally, we discuss some ethical issues, focusing on the question that how should we design robotic voices.

2 INTERACTIONAL SPEECH SYNTHESIS
2.1 Prosody Settings for Emotion and Identity
Prosody has been proven a dominant aspect to convey emotions. And in fact, prior work has succeeded in setting prosodic features for emotional speech synthesis. In [7], F0 mean (F0: fundamental frequency on which human perception of pitch depends), F0 range and tempo were increased by 50%, 100% and 30% respectively for expressing joy, and 150%, 20% and 30% for fear in German. The synthesized emotions were successfully judged by native speakers. [26] found that increasing F0 mean, F0 range, tempo, and loudness by 10 Hz, 9 semitones, 30 words per minute, and 6 decibels respectively is suitable for expressing anger in British English. [5] found log-pitch, intensity, and loudness have high correlations with arousal in four emotion corpora. In our prior work, we also observed valence has clearer correlation with pitch-related features (low, narrow and wide pitch) than other prosodic features, and arousal is also correlated with intensity and speaking rate in addition to pitch [22].

Neural text-to-speech has been widely used [24], yet adjusting prosody settings using Speech Synthesis Markup Language (SSML) [2, 31, 33] to specify parameters for intended emotion is still a typical way for robots, considering the difficulties of real-world applications. Similar to emotion, robot identity can also be formed by prosody variation. Robot identity is a long-term signal usually contains gender, age, personality, etc., and they can also be included in the SSML settings [4]. However, the majority of prior work focused on synthesizing monologues but ignored the aspects of spoken interaction which is necessary for emotion and identity. Personality is largely dependent on fillers and backchannels [6, 37], whose pragmatic meanings are highly conveyed by prosody [36]. Taking the backchannel “really” as an example, it can be used for expressing interest, surprise, or disappointment, depending on its speaking style. In conversations, utterance amount, backchannel frequency, filler frequency, and switching pause length have proven relevant to robot
personality traits [37]. [28] revealed that subjects who were less so- 
cially adept reported feeling that their robot interlocutor was more 
sincere than its human counterpart because the robot’s conversa-
tional fillers helped mitigate awkwardness and express a cooper-
ative attitude during the interaction. Here, we take backchannels 
as an example for discussion as we have studied it in human-robot 
conversation.

2.2 Backchannels

In a prior work [21], we used a female humanoid to conduct spontaneous chats with student participants. The humanoid was re-
 motely operated by a female human operator in a Wizard of Oz 
manner. The conversations between the humanoid and participants were recorded and analyzed. We focused on the following backchan-
nels: “Really?”, “Ah, I see.” and “I get it.” because we found they 
occur most frequently in the conversations. Our subjective evalu-
ation demonstrated that when generated in emotions mimicking 
the participants, the robot backchannels were perceived as natural 
and authentic compared to those without emotions. What’s more, 
we also found that even when the backchannels were generated 
with random emotions, the participants still felt the robot feedback more natural than that without emotions.

The difficulties in synthesizing backchannels are not only the lexical form, but also prosody and timing. False prosody or timing 
can cause a fatal problem in HRI. For example, imagine if a robot responds “Really?” in a happy voice when the user in fact feels sad and seeks sympathy, then the user may not want to talk to the robot anymore. The solutions lie in 1) accurately recognizing the user’s emotion and matching it, 2) accurately recognizing when to respond. Regarding 1), we noticed that even a simple emotion mapping using only happiness and disappointment corresponding to high and low valence can achieve satisfactory user experience [22]. Regarding 2), some predictive rules have been established. For example, for English backchannel generation is: Upon detection of P1, a region of pitch less than the 26th-percentile pitch level and P2, continuing for at least 110 milliseconds, P3, coming after at least 700 milliseconds of speech, P4, providing you have no output backchannel feedback within the preceding 800 milliseconds, P5, after 700 milliseconds wait, backchannels should be produced. For Japanese, some parameters are different: P1 = 28, P2 = 110, P3 = 700, P4 = 1000, and P5 = 350 [35]. As technology advances, however, these solutions will change as well.

2.3 Open Challenges

While some companies, such as Google, have successfully used syn-
thetic speech to “fool” humans on the phone1, it is still too early to 
say that robotic speech synthesis has matured to the point where it 
can respond naturally. We list the following challenges:

1. For utterances with clear lexical meanings, occasional prosody 
errors may not have a large effect on one’s evaluation of the robot. 
However, people have a much lower tolerance for the errors when it 
comes to interactional speech whose interpretation largely de-

deps on prosody, such as backchannels.

2. Detection of positions for feedback utterances is more difficult 
than that of other types of dialogue turns. For example, backchan-
nel generation requires a system to be able to process lexical and 
non-lexical aspects of an utterance, and sometimes involves related tasks such as turn-taking detection.

3. Compared to synthesizing isolated sentence utterances (the 
commonly used evaluation criteria for text-to-speech), it’s hard to 
develop a uniform rule for evaluating synthesized feedback utter-
ances as they are highly context dependent.

4. Different languages and cultures have different conventions 
for conversing. Some languages, such as Japanese, have a large 
number of fillers and backchannels. How cultural differences should 
be handled also needs to be taken into account when synthesizing 
this type of speech.

3 SCENARIO CLASSIFICATION

To the best of our knowledge, there are no uniform standards or 
best practices for designing robotic voices, not to mention its iden-
tity, and the majority of results can only represent scenarios set by 
the experiments themselves. Here, we present our scenario classi-
fication in robotic voice evaluation and explore the differences in 
their respective focus and the challenges that exist.

3.1 General Scenario

The first category is the general scenario, which typically inves-
tigates robot voice in spontaneous dialogues without considering 
specific applications. For example, in our past work, we recorded 
and analyzed daily conversations between human participants, whose 
topics include greetings, introductions, hobbies, daily life, and a lit-
tle impromptu banter. Based on the analysis results, we designed 
the robot’s emotional voice by changing the prosody and had hu-
man participants engage in conversations with it on the same top-
ics. The evaluation results showed that the human participants 
were satisfied with the robotic voice and found it to be very emo-
tionally realistic [21]. We believe such robots can be used for all 
kinds of daily chats without considering specific applications.

When designing this type of robot voice, the most critical point 
is that the voice should be real as in human sounding and meet the 
user’s preference, so that the user can feel comfortable. Past stud-
ies support this viewpoint from some aspects: Users prefer robot 
voice whose gender (male/female) matches their own [11, 19], and 
are more attracted by the robot having similar personality traits 
(introversion/extroversion) [27].

3.2 Application-Dependent Scenario

We define the second category as the application-dependent sce-
nario, which focuses on designing robotic voices for particular uses 
and expressing its identity firmly. In such cases, the emotions that 
can be expressed are limited (e.g., sad emotions that can cause 
discouragement may not be allowed in some applications such as 
team sports [18]). Taking healthcare scenario as an example, [16] 
synthesized a flat monotone and an empathetic voice via prosodic 
variation for a robot named Healthbot. They recruited 120 partic-
ipants and asked them to share their perceptions after watching 
videos of Healthbot talking in the two voices. The results reflected 
that people prefer empathetic voice for healthcare robots.

1https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html
Another example is the instruction scenario. [10] recruited student participants to evaluate a new robotic operating system by rating their perceptions towards the robotic voice, which was created as an older male voice by using a text-to-speech program. Ten participants were asked to indicate the perceived age of the robotic voice. Results indicated that higher age-identified students rated the older robotic voice higher for credibility, social presence and reported more motivation to learn. Perhaps the older male voice sounds like a “professor” or “instructor” role identity.

We believe these phenomena are caused by consensus, where we unconsciously assume that certain voices and languages have specific identity/professional attributes [8, 9, 13].

3.3 Culture-Dependent Scenario

Many past studies have demonstrated differences in the perception of robots by participants from different countries [14, 17, 23]. Nevertheless, few studies have discussed in depth the reasons behind this, leading to an open question: how to design robotic voices for different regional/cultural populations. Accordingly, we define the third category as the culture-dependent scenario.

Take Japan, for example, which is the most popular country in the world for robots. Japan has been influenced by Confucianism, Buddhism, and indigenous Shintoism for a long time, and believes that every object has a soul. Based on this culture, Japanese robots such as ASIMO [30] and ERICA [12], are generally more like real people. Besides, as the birthplace of manga comic culture, Japanese are very accepting of non-human features. For instance, the voice of humanoid Pepper in SoftBank stores is designed to resemble an anime robot. Moreover, according to the Global Gender Gap Report, Japan has the largest gender gap among all developed countries, and this is reflected in the labor force. The ratio of male to female labor force is 73%, and the vast majority of front desk, reception, and wait staff are female. Perhaps due to this special culture, receptionist robots in Japan are designed to have a female voice almost by default.

Therefore, the evaluation results obtained by participants from one cultural background cannot simply be applied to other situations.

3.4 Open Challenges

Unlike interactional speech synthesis, which focuses on technical challenges, scenario classification considers more design-level challenges:

1. The perception of robot emotion and identity is not only affected by its voice but also visual appearance. Giving a mismatched voice to a robot might introduce a confounding effect [25].
2. Is there any other classification design that can more comprehensively cover the scenario of robotic speech synthesis?
3. Associating voice with identity perception will inevitably raise ethical and social debates. Does assigning a robot voice based on human experience create bias?

4 ETHICAL AND SOCIAL ISSUES

People are not yet too concerned about current problems that exist in robotic speech and have a high tolerance for robot speech errors. Based on developments in the field of speech technology and HRI, we list the following ethical issues that we think will be gradually discussed in near future.

4.1 Language Bias

It is well known that robotic speech synthesis usually follows automatic speech recognition. Therefore, one of the major issues of robotic speech synthesis is caused and shared by the language bias of speech recognition. Speech recognition has been developed for many years yet is still limited by the availability of training data. Languages that spoken by a large population, such as English and Chinese, are relatively mature for speech recognition and can achieve similar performance as human speech recognition in specific scenarios. However, the performance for minority languages remains high, which inevitably leads to inaccurate robotic speech synthesis and thus affects the user experience. The same is true for accents and dialects.

4.2 Identity Bias

As mentioned in Section 3.2, older male voice are considered to have higher credibility and more suitable for instructor robots in some cases. Similar situation also occurs with other robotic identities, such as caregivers. Is this practice of tying voice to identity harmful for society? If these settings are widely used, will they in turn affect career choices in human society?

4.3 Gender Bias

As mentioned in Section 3.3, there are serious gender differences in some regions, resulting in the robotic voice that uses almost exclusively one gender in certain situations. Even if this is culturally acceptable to the majority of the local population, is there a gender bias involved in such design? Conversely, if the voice of male and female were used fairly, would the people of the region be willing to accept these robots?

4.4 Aesthetic Bias

In today’s society, where aesthetic diversity is prized, will the aesthetics and preferences of voice also become a topic of discussion? If so, how should we design voice timbre when synthesizing robotic voices? Should they be associated with the appearance of the robot? For example, should a robot with a cute appearance always generate a sweet tone?

5 CONCLUSION

In this paper, we present new perspectives to answer this question: how should we synthesize robotic voices to meet the needs of different situations? Firstly, we point out the difficulties of synthesizing interactional utterances that are highly frequent in dialogue speech, particularly backchannels. Secondly, we provide a novel scenario classification scheme for speech and robot researchers to better design robotic voices. Lastly, we discuss some ethical and social
issues that may have not been mentioned yet. We hope our discussion can bring attention in HRI community for better robotic speech synthesis.

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REFERENCES

[1] Sames Al Moubayed, Malek Baklouti, Mohamed Chetouani, Thierry Dutout, Ammar Mahdouani, J-C Martin, Stanislav Ondas, Catherine Pelachaud, Jérôme Ubrain, and Mehmet Yilmaz. 2009. Generating robot/agent backchannels during a storytelling experiment. In 2009 IEEE International Conference on Robotics and Automation. IEEE, 3749–3754.

[2] Paolo Baggio, Paul Bagshaw, Michael Bodell, De Zhi Huang, Lou Xiaoian, Scott McGlashan, Jianhua Tao, Yan Jun, Hu Fang, Yongguo Kang, et al. 2010. Speech synthesis markup language (SSML) version 1.1. World Wide Web Consortium, Recommendation REC-speechsynthesis11-20100907 (2010).

[3] Sandra Bedaf, Patrizia Marti, Farshad Amirabollahian, and Luc de Wette. 2018. A multi-perspective evaluation of a service robot for seniors: the voice of different stakeholders. Disability and rehabilitation: assistive technology 13, 6 (2018), 592–599.

[4] Oliver Bendel. 2017. SSML for sex robots. In International Conference on Love and Sex with Robots. Springer, 1–11.

[5] Daniel Bone, Chi-Chun Lee, and Shrikranth Narayanan. 2014. Robust unsupervised arousal rating: A rule-based framework with knowledge-inspired vocal features. IEEE transactions on affective computing 5, 2 (2014), 201–213.

[6] Carolin Brück, Benjamin Kreifelts, Evangelia Kaza, Martin Lotzine, and Dirk Wildgruber. 2011. Impact of personality on the cerebral processing of emotional prosody. Neuroimage 58, 1 (2011), 259–268.

[7] Felix Burkhart and Walter F Sendineiner. 2000. Verification of acoustical correlates of emotional speech using formant-synthesis. In ISCA Tutorial and Research Workshop (ITRW) on speech and emotion.

[8] Carol M Eastman. 1985. Establishing social identity through language use. Style and sociolinguistic variation (RO-MAN). 13, 6 (2018), 592–599.

[9] Penelope Eckert and John R Rickford. 2001. Style and sociolinguistic variation. Cambridge University Press.

[10] Chad Edwards, Autumn Edwards, Brett Stoll, Xialing Lin, and Noelle Massey. 2019. Evaluations of an artificial intelligence instructor’s voice: Social Identity Theory in human-robot interactions. Computers in Human Behavior 90 (2019), 357–362.

[11] Friederike Eysel, Laura De Ruiter, Dieta Kuchenbrandt, Simon Bobinger, and Frank Hegel. 2012. 'If you sound like you, must be more human': On the interplay of robot and user features on human-robot acceptance and anthropomorphism. In 2012 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 125–126.

[12] Dylan F Glas, Takashi Minato, Carlos T Iishi, Tatsuya Kawahara, and Hiroshi Ishiguro. 2016. Erica: The erato intelligent conversational android. In Proceedings of the 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 125–126.

[13] Jette G Hansen and Jun Liu. 1997. Social identity and language: Theoretical and methodological issues. TESOL Quarterly 31, 3 (1997), 567–576.

[14] Kerstin Sophie Haring, David Silvera-Tawil, Yoshio Matsumoto, Mari Velonaki, and Katsumi Watanabe. 2014. Perception of an android robot in Japan and Australia: A cross-cultural comparison. In International conference on social robotics. Springer, 166–175.

[15] Nusrat Hussain, Engin Erzin, T Metin Sezgin, and Yuce Yener. 2019. Speech driven backchannel generation using deep q-network for enhancing engagement in human-robot interaction. arXiv preprint arXiv:1908.01618 (2019).

[16] Jesin James, BT Balamurali, Catherine F Watson, and Bruce MacDonald. 2020. Empathetic Speech Synthesis and Testing for Healthcare Robots. International Journal of Social Robotics (2020), 1–19.

[17] Frédéric Kaplan. 2004. Who is afraid of the humanoid? Investigating cultural differences in the acceptance of robots. International journal of human-robotic 1, 03 (2004), 465–480.

[18] Divesh Lala, Yuanchao Li, and Tatsuya Kawahara. 2017. Utterance Behavior of Users While Playing Basketball with a Virtual Teammate. In ICAART (1) (2017), 28–38.

[19] Eun Ju Lee, Clifford Nass, and Scott Brave. 2000. Can computer-generated speech have gender? An experimental test of gender stereotype. In CHI’00 extended abstracts on Human factors in computing systems. ACM, 289–290.

[20] Younggun Lee, Azam Babaei, and Seo-Young Lee. 2017. Emotional end-to-end neural speech synthesizer. arXiv preprint arXiv:1711.05447 (2017).

[21] Yuanchao Li, Carlos Toshinori Ishi, Koji Inoue, Shizuka Nakamura, and Tatsuya Kawahara. 2019. Expressing reactive emotion based on multimodal emotion recognition for natural conversation in human-robot interaction. Advanced Robotics 33, 20 (2019), 1030–1041.

[22] Yuanchao Li, Carlos Toshinori Ishi, Nigel Ward, Koji Inoue, Shizuka Nakamura, Katsuya Takanashi, and Tatsuya Kawahara. 2017. Emotion recognition by combining prosody and sentiment analysis for expressing reactive emotion by humanoid robot. In 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 1356–1359.

[23] Velvetina Lim, Maki Rooksby, and Emily S Cross. 2021. Social robots on a global stage: establishing a role for culture during human-robot interaction. International Journal of Social Robotics 13, 6 (2021), 1307–1333.

[24] Zhen-Hua Ling, Shi-Yin Kang, Heiga Zen, Andrew Senior, Mike Schuster, Xiao-Jun Qian, Helen M Meng, and Li Deng. 2015. Deep learning for acoustic modeling in parametric speech generation: A systematic review of existing techniques and future trends. IEEE Signal Processing Magazine 32, 3 (2015), 35–52.

[25] Conan McGinn and Ilaria Torre. 2019. Can you tell the robot by the voice? an exploratory study on the role of voice in the perception of robots. In 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 211–212.

[26] Iain R Murray and John L Arnott. 1995. Implementation and testing of a system for producing emotion-by-rule in synthetic speech. Speech Communication 16, 4 (1995), 369–390.

[27] Clifford Ivar Nass and Scott Brave. 2005. Wired for speech: How voice activates and advances the human-computer relationship. MIT press Cambridge, MA.

[28] Naoki Ohashima, Keita Kimijima, Junji Yamato, and Naoki Mukawa. 2015. A conversational robot with vocal and bodily fillers for recovering from awkward silence at turn-takings. In 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN). IEEE, 325–330.

[29] Hae Won Park, Mirko Gelsomini, Jin Joo Lee, Tonghui Zhu, and Cynthia Breazeal. 2017. Backchannel opportunity prediction for social robot listeners. In 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2508–2514.

[30] Satoshi Shigemi, Ambarish Goswami, and Prabhad Vadakkepat. 2018. ASIMO and humanoid robot research at Honda. Humanoid robotics: A reference (2018), 55–90.

[31] Paul Taylor and Amy Isard. 1997. SSML: A speech synthesis markup language. Speech communication 22, 3 (1997), 293–312.

[32] Néstor Titi, Kevin El Haddad, and Thierry Dutot. 2019. Exploring transfer learning for low resource emotional tts. In Proceedings of SAI Intelligent Systems Conference. Springer, 52–60.

[33] Mark W Walker, Jim Larson, and Andrew Hunt. 2001. A new W3C markup standard for text-to-speech synthesis. In 2001 IEEE International Conference on Acoustics, Speech, and Signal Processing, Proceedings (Cat. No. 01 CH37221). Vol. 2, IEEE, 965–968.

[34] Michael L Walters, Dag Sverre Syrdal, Kheng Lee Koay, Kerstin Dautenhahn, and René Te Boekhorst. 2008. Human approach distances to a mechanical-looking robot with different robot voice styles. In 2008 RO-MAN: The 17th IEEE International Symposium on Robot and Human Interactive Communication. IEEE, 707–712.

[35] Nigel Ward and Wataru Tsukahara. 2000. Prosodic features which cue backchannel responses in English and Japanese. Journal of pragmatics 32, 8 (2000), 1177–1207.

[36] Nigel Ward, Yuanchao Li, Tianyu Zhao, and Tatsuya Kawahara. 2016. Inter- and pragmatics-related prosodic patterns in Mandarin dialog. In Speech prosody.

[37] Kenta Yamamoto, Koji Inoue, Shizuka Nakamura, Katsuya Takanashi, and Tatsuya Kawahara. 2018. Dialogue behavior control model for expressing a character of humanoid robots. In 2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 1732–1737.