HOW SIMILAR OR DIFFERENT IS RAKUGO SPEECH SYNTHESIZER TO PROFESSIONAL PERFORMERS?

Shuhei Kato*,†, Yusuke Yasuda*, Xin Wang*, Erica Cooper*, Junichi Yamagishi*

*National Institute of Informatics, Japan †The Graduate University for Advanced Sciences, Japan

ABSTRACT

We have been working on speech synthesis for rakugo (a traditional Japanese form of verbal entertainment similar to one-person stand-up comedy) toward speech synthesis that authentically entertains audiences. In this paper, we propose a novel evaluation methodology using synthesized rakugo speech and real rakugo speech uttered by professional performers of three different ranks. The naturalness of the synthesized speech was comparable to that of the human speech, but the synthesized speech entertained listeners less than the performers of any rank. However, we obtained some interesting insights into challenges to be solved in order to achieve a truly entertaining rakugo synthesizer. For example, naturalness was not the most important factor, even though it has generally been emphasized as the most important point to be evaluated in the conventional speech synthesis field. More important factors were the understandability of the content and distinguishability of the characters in the rakugo story, both of which the synthesized rakugo speech was relatively inferior at as compared with the professional performers. We also found that fundamental frequency ($f_0$) modeling should be further improved to better entertain audiences. These results show important steps to reaching authentically entertaining speech synthesis.

Index Terms—Entertainment, listening test, rakugo, speech synthesis, text-to-speech

1. INTRODUCTION

Entertainment has been essential to human beings since ancient times. While the role of the performer, a person who entertains people by acting, singing, dancing, or playing music [1], has been carried out by human beings almost exclusively for a long time, machines are beginning to carry out the role today, e.g., singing voice synthesizers [2, 3, 4] and dancing robots [5, 6]. In the field of verbal entertainment, we have focused on rakugo, which is a traditional Japanese form of verbal entertainment similar to one-person stand-up comedy and is popular even today, and we have developed rakugo speech synthesizers based on the Tacotron framework [7, 8]. One open question is how to evaluate rakugo speech synthesizers. We can easily imagine that the standard listening test for naturalness is not sufficient for this purpose. Are there any good ways to benchmark their performance?

In Japan, professional rakugo performers are ranked at one of three levels [1] i.e., zenza (minor performer), futatsume (second-rank performer), and shin-uchi (first-rank performer). In our previous study [8], we used a shin-uchi performer’s audio recordings only as a reference for assessing our synthesizer. However, such evaluation may not be ideal since the skills of rakugo performers also vary significantly. We should compare rakugo speech synthesizers with rakugo performers from the three different ranks. This should clarify what is missing in our rakugo synthesizer to entertain audiences more precisely.

In this paper, we therefore propose a novel subjective evaluation methodology using natural speech uttered by performers from the three different ranks in addition to synthesized speech and show benchmarking results for our rakugo speech synthesizer. For this purpose, we recorded speech of a common story performed by a performer of each of the three ranks and then conducted a subjective comparison with synthesized speech of the same story in terms of five aspects: 1) naturalness, 2) distinguishability of characters in the story, 3) understandability of content, 4) degree of entertainment, and 5) performer’s skill level.

This paper is structured as follows. In Section 2, we explain the ranks of professional performers in rakugo. We describe audio data collected for this evaluation and our end-to-end TTS system in Sections 3 and 4, respectively. We then explain our evaluation methodology and its benchmark results in Section 5. Acoustic analysis results are shown in Section 6, and we summarize our findings in Section 7.

2. RANKS OF PROFESSIONAL PERFORMERS IN EDO RAKUGO

Rakugo is divided into Edo (Tokyo) rakugo and Kamigata rakugo, which was developed in Osaka and Kyoto. In this paper, we focus on Edo rakugo. Edo rakugo has a three-rank

---

1 A more precise ranking is Kamigata shin-uchi (Tokyo) rakugo, which we focus on in this paper, has a class system, while Kamigata rakugo, which was developed in Osaka and Kyoto, does not today.
class system. In ascending order, professional rakugo performers are ranked at either *zenza*, *futatsume*, or *shin-uchi*. It generally takes three to five years to be promoted from *zenza* to *futatsume* and about ten years to be promoted from *futatsume* to *shin-uchi*. As of 2020, about 600 professional performers are active in Edo rakugo [9][10][11][12].

3. AUDIO RECORDINGS

How high is the skill level of our rakugo speech synthesizer compared with professional rakugo performers? To investigate this, we recorded the performances of a common story told by professional performers of the three ranks.

The recordings were carried out in January 2020. The performers were Yanagiya Kogoto (*zenza*), Ryutei Ichido (*futatsume*), and Yanagiya Sanzi (*shin-uchi*), the same performer who performed for the database used in the speech synthesis model training [8]). The recording conditions were the same as those of the recordings for the database. Each performer performed alone in a recording booth, and he did not face or receive any reactions from an audience. The story performed by them is called “Misomame.” The total durations of the recordings by the *zenza*, *futatsume*, and *shin-uchi* were 2.5, 2.7, and 4.2 minutes, respectively. To record performances that sound as natural as possible, we did not re-record any of the stories when mispronunciations or restatements occurred, except in cases where the performer asked us to do so.

4. SPEECH SYNTHESIS MODEL

We used a variant of the Tacotron-based TTS system (SA-Tacotron-context model from our previous study [8]) because this model was evaluated as the best one. This model takes textual information and context embeddings as inputs. It should be noted that the model is based on speech by the *shin-uchi* performer recorded in 2017, and the newly recorded speech in Section 3 was not used for model building and was used only for comparison with synthesized speech. Please refer to [8] for details on the features, network structure, training conditions, etc. Minor differences from [8] were as follows. 1) The sentences in “Misomame” were excluded from the training set and validation set. As a result, we used 6,362 sentences (3.67 hours) for training, 706 sentences (0.42 hours) for validation, and 273 sentences (0.22 hours) for testing. 2) The sampling frequency was changed from 16kHz to 24kHz for mel-spectrogram output from the speech synthesis model and waveforms generated through a WaveNet vocoder [13][14][15]. Accordingly, the frame shift and fast Fourier transform size were changed to 12 ms and 2,048, respectively.

5. LISTENING TEST FOR BENCHMARK

To benchmark the level of our rakugo speech synthesis, we designed a new listening test and conducted a large-scale listening test as described below.

5.1. Test conditions

Speech of “Misomame” was used in the test, although speech of shorter stories was used for a listening test in our previous study. The reason is that we believe a “full” story is more suitable for evaluating the level of rakugo speech synthesis than a short story. We therefore adopted “Misomame,” which is a full story, though relatively short in duration, on the basis of advice from Yanagiya Sanza, the *shin-uchi* performer above.

The speech was synthesized sentence by sentence. Pauses between sentences were not predicted and the pauses between sentences for the synthesized speech were the same as those of the real audio recording. Listeners evaluated the speech not sentence by sentence but as a whole story. All speech was normalized to −26 dBov over the whole story using sv56 [16].

We asked listeners to answer a five-scale mean opinion score (MOS) based test. Listeners listened to either speech by the professional performers (zenza, *futatsume*, or *shin-uchi*) or the synthesized speech, and they evaluated them according to the five questions below.

1) How natural did the performer sound?
2) How accurately did you think you could distinguish each character?
3) How well did you think you could understand the content?
4) How well were you entertained?
5) How high was the rakugo skill level of the performer?

The most important question was Q4 since rakugo is a form of verbal entertainment. Q5 was intended for evaluating the “skill level” of the rakugo speech synthesis as if it were a professional performer. The others were questions about factors that we hypothesized may affect the results of Q4 and Q5. A total of 292 listeners participated in 292 evaluation rounds.

5.2. Results

The listening test results are shown in Fig. 1 where SS, NS, NF, and NZ correspond to speech synthesis, *shin-uchi*, *futatsume*, and *zenza*, respectively. For statistical analysis, we used a Brunner-Munzel test [17] with Bonferroni correction. As can be seen from the figure, the scores of the speech synthesis did not reach those of the natural speech of the professional performers, but we see that the trends in the score differences were different depending on the question.

---

Specific wording depends on performers because rakugo stories do not have any scripts.

The *shin-uchi* performer attended the recording session of the *zenza* performer, and he supervised and instructed the *zenza* performer when necessary.

4While there is no clear definition either of a full rakugo story or short story, short stories tend to appear in the makura, or prelude to the main story, of the performance of a full story, and are never independently performed on a stage. In Edo rakugo, several hundred traditional stories are performed.

5They should be predicted, but that is out of the scope of this paper.
For Q1 (naturalness), the mean score for the speech synthesis was 4.0. This means that the naturalness of the synthesized speech was high and comparable enough to that of natural speech. On the contrary, for Q2 (character), Q3 (content), and Q4 (entertaining), the mean scores for the speech synthesis ranged between 3.0 and 4.0, which were much lower than those for the professional performers. For Q3 and Q4, the p-values between the scores for the speech synthesis and those for the zenza were also smaller than the p-values between the scores for the speech synthesis and those for the futatsume or shin-uchi.

For Q5, which measures the skill level of the performer, the mean scores descended according to rank (shin-uchi > futatsume > zenza) as we expected. The synthesized speech was rated lower than the natural performances.

5.3. Correlations among questions
To understand the listening test results better, we calculated the correlation coefficients of the MOSs among the questions, and the results are shown in Table 1. We see that the Q4 (entertaining) scores had a larger correlation coefficient in the order of the scores for Q5 (skill), Q3 (content), Q2 (character), and Q1. In other words, Q1 (naturalness) had the weakest correlation coefficient with Q4 (entertaining). The correlation coefficient between the scores for Q2 and those for Q3 was also relatively large. In summary, while the skill level (Q5), entertainment (Q4), understandability (Q3), and distinguishability of the characters (Q2) were correlated with each other to a moderate degree, naturalness (Q1) appeared to be less correlated with the other metrics.

From the above results in Fig. 1, we learned that, even though the naturalness of the synthesized rakugo speech was close to that of the human professionals, it could not sufficiently entertain the listeners because the listeners could not perfectly distinguish characters in the synthesized speech and therefore could not adequately understand the content. In other words, we should not only improve the naturalness of synthesized speech but also refine the modeling of other aspects of speech, such as the distinguishability of characters in the case of rakugo, to better entertain listeners.

### Table 1. Correlation coefficients of MOSs between questions.

|        | Q2   | Q3       | Q4       | Q5 (skill) |
|--------|------|----------|----------|------------|
| Q1 (naturalness) | 0.287 | 0.303    | 0.317    | 0.339      |
| Q2 (character)    | -    | 0.538    | 0.486    | 0.580      |
| Q3 (content)      | -    | -        | 0.597    | 0.582      |
| Q4 (entertaining) | -    | -        | -        | 0.656      |

6. ACOUSTIC ANALYSIS
We further investigated what makes it difficult for listeners to distinguish characters. We calculated the mean and standard deviation of the logarithmic $f_0$ ($\ln f_0$) and duration per mora, sentence by sentence, and averaged them over the story for
Fig. 2. Means of means and standard deviations of logarithmic fundamental frequency (ln\(f_0\)) over each sentence. \textit{Sadakichi} and \textit{Danna} are two characters performed by performers.

Fig. 3. Means of means and standard deviations of duration per mora over each sentence. SS (modified) was calculated on basis of sentences, excluding two sentences for which duration was estimated as too long.

each character. \textit{Misomame} has two characters, \textit{Sadakichi} (a boy) and \textit{Danna} (a middle-aged male). The results for the ln\(f_0\) and duration corresponding to the two characters in the test set are shown in Figs. 2 and 3.

In Fig. 2, we can see that the cross-character difference for the mean ln\(f_0\) of the synthesized speech was smaller than that of the human professionals’ speech, particularly that of the futatsume’s speech. We should consider that the extent to which a performer differentiates the voices of different characters depends on the performer. Yanagiya Sanza, the shin-uchi performer, does not strongly distinguish characters, according to an interview [18]. However, the difference for the synthesized speech was even smaller than that of the shin-uchi performer. We could therefore conclude that our speech synthesis does not have sufficient enough ability to distinguish characters using \(f_0\).

In Fig. 3, we can see that all of the human professionals did not strongly distinguish characters using speech rates in the case of “Misomame.” This was the same for speech synthesis. We would like to note that professional perform-

In this paper, we proposed a novel methodology for evaluating rakugo speech and conducted a listening test to investigate how the level of rakugo speech synthesis compares to professional rakugo performers at various levels. From the listening test results, we found that the level of speech synthesis did not reach that of human professionals. The results suggest, however, that we should make the \(f_0\) expression of speech synthesis richer to better entertain audiences.

In future work, we will design a speech synthesis architecture and training framework that can better distinguish characters. The frequency of the properties of the characters (gender, age, social rank, etc.) in common rakugo stories, however, is very unbalanced. For example, young townsmen appear in rakugo stories very frequently, and women servants to samurai warriors rarely appear. We should consider such imbalance when designing a model. We will also work on other issues to be solved, such as estimating pauses between sentences and visual synthesis.

6Rakugo is essentially a form of audio-visual entertainment.
8. REFERENCES

[1] C. McIntosh, Ed., *Cambridge Advanced Learner’s Dictionary*. Cambridge University Press, Jun 6 2013.

[2] Yamaha Corporation, *VOCALOID*, 2004–present.

[3] CeVIO, *CeVIO Creative Studio*, 2013–present.

[4] NEUTRINO. *NEURAL SINGING SYNTHESIZER*, 2020.

[5] Sharp Corporation, *RoBoHoN*, 2016–present.

[6] XINGO: *Bluetooth Dancing Robot Speaker*, 2020.

[7] S. Kato, Y. Yasuda, X. Wang, E. Cooper, S. Takaki, and J. Yamagishi, “Rakugo speech synthesis using segment-to-segment neural transduction and style tokens — toward speech synthesis for entertaining audiences,” in *Proc. 10th ISCA Speech Synthesis Workshop (SSW10)*, Vienna, Austria, 2019, pp. 111–116.

[8] ———, “Rakugo speech synthesis and its limitations: Toward speech synthesis that entertains audiences,” *IEEE Access*, vol. 8, pp. 138 149–138 161, 2020.

[9] Rakugo Kyokai, “Geinin shokai (in Japanese).” [Online]. Available: https://rakugo-kyokai.jp/variety-entertainer/

[10] Rakugo Geijutsu Kyokai, “Kyokaiin profile (in Japanese).” [Online]. Available: https://www.geikyo.co.jp/profile/

[11] Tokyo Kawaraban, *Toto Yose Engeika Meikan (in Japanese)*. Tokyo Kawaraban, 2018.

[12] Rakugo Tatekawa-Ryu, “Tatekawa-ryu no rakugokat-achi (in Japanese).” [Online]. Available: http://tatekawa.info/member/

[13] A. van den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, “WaveNet: A generative model for raw audio,” arXiv:1609.03499 [cs.SD], Sep 12 2016.

[14] X. Wang, J. Lorenzo-Trueba, S. Takaki, L. Juvela, and J. Yamagishi, “A comparison of recent waveform generation and acoustic modeling methods for neural-network-based speech synthesis,” in *Proc. Int. Conf. on Acoust., Speech, and Signal Process. (ICASSP)*, Calgary, AB, Canada, Apr 15–20 2018, pp. 4804–4808.

[15] A. Tamamori, T. Hayashi, K. Kobayashi, K. Takeda, and T. Toda, “Speaker-dependent WaveNet vocoder,” in *Proc. INTERSPEECH*, Stockholm, Stockholm, Sweden, Aug 20–24 2017, pp. 1118–1122.

[16] Int. Telecommun. Union, Recommendation G.191: Software Tools and Audio Coding Standardization, Nov 11 2005.

[17] E. Brunner and U. Munzel, “The nonparametric Behrens-Fisher problem: Asymptotic theory and a small-sample approximation,” *Biometrical J.*, vol. 42, no. 1, pp. 17–25, Jan 2000.

[18] Tokyo Bar Association, “Interview: Yanagiya sanza, a professional rakugo performer (in Japanese),” *LIBRA*, vol. 11, no. 11, pp. 22–25, 2011.

[19] S. Kato, S. Takaki, J. Yamagishi, and X. Wang, “Investigation of rakugo speech synthesis and analysis of context using wavenet: Toward speech synthesis entertaining people (in Japanese),” in *Proc. 2018 ASJ Autumn Meeting*, Oita, Oita, Japan, 2018, pp. 1139–1142.

[20] L. van der Maaten and G. Hinton, “Visualizing data using t-SNE,” *J. Mach. Learn. Res.*, vol. 9, pp. 2579–2605, Nov 2008.

[21] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, and S. Khudanpur, “X-vectors: Robust DNN embeddings for speaker recognition,” in *Proc. Int. Conf. Acoust., Speech, and Signal Process. (ICASSP)*, Calgary, AB, Canada, Apr 15–20 2018, pp. 5329–5333.