ACCENT ESTIMATION OF JAPANESE WORDS FROM THEIR SURFACES AND ROMANIZATIONS FOR BUILDING LARGE VOCABULARY ACCENT DICTIONARIES

Hideyuki Tachibana  Yotaro Katayama
PKSHA Technology Inc., Hongo, Bunkyo, Tokyo, Japan

ABSTRACT
In Japanese text-to-speech (TTS), it is necessary to add accent information to the input sentence. However, there are a limited number of publicly available accent dictionaries, and those dictionaries e.g. UniDic, do not contain many compound words, proper nouns, etc., which are required in a practical TTS system. In order to build a large scale accent dictionary that contains those words, the authors developed an accent estimation technique that predicts the accent of a word from its limited information, namely the surface (e.g. kanji) and the yomi (simplified phonetic information). It is experimentally shown that the technique can estimate accents with high accuracies, especially for some categories of words. The authors applied this technique to an existing large vocabulary Japanese dictionary NEologd, and obtained a large vocabulary Japanese accent dictionary. Many cases have been observed in which the use of this dictionary yields more appropriate phonetic information than UniDic.

Index Terms— Text-to-speech, accent, Japanese, neural networks, attention.

1. INTRODUCTION
Japanese text is composed of variety of characters, and each character is pronounced in various ways depending on the context. Therefore, the first task of Japanese TTS is to convert the raw text into some phonetic information as follows, using some dictionaries.

raw text: 筆の端で筆をつつく。
yomi: hashi no hashi de hashi o tsutsuku.

However, the standard Hepburn romanization, which we call ‘yomi’ in this paper, is not sufficient yet, as it lacks of the accent information of each word, which sometimes even changes the meaning of it (see Table 1). Therefore, we need to insert appropriate accent marks as follows,

phonetic: ha[shi no ha[shi de ha[shi o tsu[tsu]ku.

where the brackets “[” and “]” indicate “raise the pitch” and “lower the pitch,” respectively. Intuitively, it is pronounced like the ‘melody’ shown in Fig. 1.

This paper is based on results obtained from a project subsidized by the New Energy and Industrial Technology Development Organization (NEDO).

1 Yomis are often written in kana characters (hiragana or katakana), but we show them using Latin letters (romaji) in this paper for readability. Kana and romaji are essentially almost the same.

2 It has been common in Japanese TTS systems to use the binary pitch model that the pitch of a mora is either H (high) or L (low). However, some linguists claim that the model based on [ ] and [ ] is closer to the actual speech. See e.g. Uwano’s articles [1, 2].

Table 1. Examples of Japanese words whose meaning depend on the accents in Tokyo dialect.

| surface | yomi | accent (Tokyo) | meaning |
|---------|------|----------------|---------|
| 酒 | sake | sake | alcoholic beverage |
| 鰤 | sake | sake | salmon |
| 藤 | fuji | fuji | wisteria |
| 富士 | fuji | Mt. Fuji |
| 玉 | tama | tama | ball |
| 多摩 | tama | tama | Western Tokyo |
| 伝記 | denki | de[nki | biography |
| 電気 | denki | de[nki | electricity |

Table 2. Examples of words that MeCab+UniDic does not analyze correctly.

| surface | correct yomi | wrong yomi based on UniDic |
|---------|--------------|---------------------------|
| 一日千秋 | ichijitsuyokoushu | ichi nichi chikus |
| 閑静付け | omiotsuke | go go go tsuke |
| 36協定 | satoriyoden | yama tokyo den |
| 県立大学千代田 | agatanosakainonichigo | ken inukai michiyo |
| 谷崎亮孔明 | shokatsu ryokomin | shokatsu ryu hiroaki |
| 十勝山 | hachiman/yma | yamada yama |
| 本八幡 | mototawata | hon hachiman |
| 武蔵嵐山 | masashiranzan | masashi arashiyama |
| 二の二階 | rinshinkashikou | re ji kua |

Fig. 1. Concept of Japanese accent. Each note indicates a mora.

Since the accent marks are not explicitly written in the raw text nor the yomi, we need to look them up in some dictionaries, but the number of accent dictionaries publicly available is limited. At the moment, UniDic [3, 4, 5], an open source Japanese dictionary for a text analyzer MeCab [6], is one of the few options, but it has a shortcoming that many words are intentionally excluded, e.g., compound words, proper nouns, idiomatic phrases, numerals, technical terms, etc. because of its policy to prioritize the linguistic consistency. As the cost of that, it often fails to give the correct yomis to some compound words and proper nouns e.g. shown in Table 2. Thus we need a dictionary that contains those words and their correct yomis and accents.

The objective of this paper is to propose a technique for building a large scale Japanese accent dictionary that covers such words, using limited information of them, viz. their surfaces and yomis. Fortunately, there already exists NEologd [7, 8], a web crawling-based large scale dictionary for MeCab, which is recently very pop-
ular in Japanese NLP. The dictionary contains millions of pairs of surfaces and yomis, and thus, we may construct a large scale accent dictionary just by applying our technique to it. To our knowledge, there has not been such a large vocabulary Japanese accent dictionary whose vocabulary size is as large as several millions.

2. RELATED WORK

In both linguistics and engineering, there have been many studies on accent of Japanese. Of these, Sagisaka’s rule \[9\] would be a well-established classic in the engineering community, and it (and its complements and extensions e.g. \[10\] \[11\]) has been exploited in many Japanese TTS systems and related applications, e.g. GalateaTalk \[12\], OpenJTalk, Orpheus \[13\], etc. A shortcoming of such rule-based approaches is that the users need to enter the grammatical information of the neologisms correctly when they are going to add them to a custom dictionary.

In addition to those rule-based approaches, some statistical techniques are also proposed. For example, Nagano et al. proposed N-gram based technique \[14\], and Minematsu, Suzuki et al. proposed a technique based on CRF \[15\] \[16\]. The CRF-based technique implicitly assumes that a text analyzer can separate a sentence into morphemes correctly, which is not always the case, as shown in Table \[2\].

Other machine learning-based techniques include Bruguier’s \[17\] method based on LSTM and an attention mechanism. The objective of the study is to construct an accent dictionary but the input data are different from ours; it exploits audio data, as well as yomi. Comparing to those existing methods, the advantages of our method would be as follows: (1) The user is required to enter only the accessible information of the word, namely the surface and the yomi, when adding it to the custom dictionary. (2) Our technique could be robust against the errors of McCab+UniDic, as it searches somewhat plausible morphology from several candidates exploiting both surface and yomi. (3) We ‘pre-render’ the accents of the compound words, proper nouns, etc., as many as possible, and list them in the dictionary. Without postprocessing modules that estimate the accent sandhi, the dictionary alone gives the plausible accents of those words. This will make the system simpler. (4) We could exploit NEologd as a basis, which is a popular dictionary in the open-source ecosystem of Japanese NLP. Although further improvements are needed, we can obtain a very large scale accent dictionary at once.

3. PROBLEM DEFINITION

Let us assume that the surface \( s \) and the yomi \( y \) of a word are given. For example, \((s,y) = (深層學習, shinsōgakushū)\) (meaning ‘deep learning’). Note, using a simple subroutine, the yomi is mutually converted to a sequence of morae, so we also denote it as \( y \), i.e.,

\[
y = [\text{shi}, N, \text{so}, o, ga, ku, shu, u]^T.
\]

Our target is the accent \( \alpha \in \{+1, -1, 0\}^{[4]} \)

\[
\alpha = [\text{shi}, \text{N}, \text{so}, o, \text{ga}, \text{ku}, \text{shu}, 0, 0, 0]^T,
\]

where \(+1\) and \(-1\) indicate \([\) and \(]\), respectively. Our objective is to construct a function \( f : (s, y) \rightarrow \alpha \) using triples \( \{(s_i, y_i, \alpha_i)\} \).

The problem setting is reasonable for the following two reasons. Firstly, let us consider a case where a native/fluent speaker is trying to add a newly-coined word (e.g. the name of their new product) to a custom dictionary. In this case, it may not be expected that they can enter neither the accent, (native/fluent speakers are not necessarily conscious of the accents of words), nor the grammatical information of the word i.e. POS tag, goshu \[9\] sandhi (liaison) rules, and accent sandhi type \[5\] \[9\]. However, we can expect that most native/fluent speakers at least know the surface and the yomi of the word they are going to add to their custom dictionary. Secondly, there already exists a large size dictionary publicly available, viz., NEologd, which contains approx 3 million pairs \((\{s^{(i)}, y^{(i)}\})_{1 \leq i \leq 3 \times 10^6}\).

4. ACCENT ESTIMATION TECHNIQUE

4.1. Feature Extraction from Surface \( s \)

Instead of using a raw \( s \), we may extract detailed linguistic information from \( s \) using McCab+UniDic \[4\]. Let \( \pi_1(s) \) be the \( r \)-th best result of McCab+UniDic analysis. In general, \( \pi_1(s) \) is not always the correct morphological segmentation of a compound word \( s \). For example, by analyzing the word \( s = \text{一日千秋} (y = \text{ichijitsuenshū}) \), we have

\[
\pi_1(s) = \begin{bmatrix}
-1 & \text{ich) \text{numeral}, C3} \\
\end{bmatrix} \begin{bmatrix}
\text{ni} & \text{ichi} & \text{suffix of numerals, C3} \\
\text{千秋} & \text{ichi} & \text{given name}
\end{bmatrix}
\]

where “C3” is the accent sandhi type \[5\] of the word. The \( \pi_1(s) \) is not correct simply because the yomi is different from \( y \). However, the 56-th best result returns the correct yomi as follows,

\[
\pi_56(s) = \begin{bmatrix}
-1 & \text{ich) \text{numeral}, C3} \\
\text{ji} & \text{jitsu} & \text{suffix, C4} \\
\text{千秋} & \text{sei} & \text{nshuu}
\end{bmatrix}
\]

In general, we may obtain a better morphological segmentation of a surface \( s \) by searching the \( \pi_i(s) \) whose yomi is close to \( y \).

On the basis of this idea, we extracted \( m \) candidates from the 20-best analysis results \( \{\pi_i(s)\}_{1 \leq i \leq 20} \) based on Levenshtein distance from \( y \), and sampled one \( \pi^*(s) \) out of those \( m \) candidates randomly for each iteration. (\( m = 3 \) during training, and \( m = 1 \) during inference.) From this obtained \( \pi^*(s) \), we extracted consonant, vowel, POS tag, goshu, accent mark and accent sandhi type for each mora, and used those information as the feature of \( s \).

4.2. Neural Network Model \( f \)

We used a simple neural network model shown in Fig. \[2\]. The network includes three trainable submodules \( f_s(\cdot), f_y(\cdot), \) and \( f_a(\cdot) \). \( f_s(\cdot) \) and \( f_y(\cdot) \) encode the surface \( \pi(s) \) and the yomi \( y \), respectively. Then the dot-product attention \[18\] aligns them, and finally, \( f_a(\cdot) \) decodes it and outputs the accent \( \alpha \).

\( \text{Goshu indicates the origin of a word, i.e., whether a word is a Japanese word, a loanword from Chinese, or Western languages, etc.} \)

\( \text{As a preprocessing, we converted all the numerals in \( s \) into kanji (for example, } \text{10234.56} \rightarrow \text{一万二千三百四十五六}) \text{ using a simple subroutine.} \)
Table 4. Comparison of UniDic and our dictionary based on NEologd. Wavy lines indicate errors.

| input text | UniDic | ours |
|------------|--------|------|
| 江戸川や多摩川、荒川、隅田川、神田川などがある。 | `江戸川` | `江戸川` |
| 本郷台の電台がら呜ら鳴る。 | `本郷台` | `本郷台` |
| Kubernetes to docker と nginx の使い方を覚える。 | `Kubernetes` | `Kubernetes` |
| ラグビー日本代表の試合を見に飛行機に行く。 | `ラグビー` | `ラグビー` |

The main body of each $f_{\alpha}^r$ was a four-layer non-causal 1D convolutional network. Additionally, $f_{\alpha}^r$ and $f_{\alpha}^r$ were preceded by the character-embedding layers, and $f_{\alpha}^r$ was followed by point-wise layers. Each convolutional layer of $f_{\alpha}^r$ was a 1D dilated convolution of kernel size 3 and channel size 64, preceded by a dropout ($p = 0.5$, followed by a batch normalization [19] and a highway activation [20] (gated residual connection). The dilation factors of the convolutions of $f_{\alpha}^r$ were $1 \rightarrow 3 \rightarrow 1 \rightarrow 3$.

The objective function was the cross entropy between the predicted density $p_\theta$ and the smoothed ground truth $p_{\mathrm{gt}}$ [21] [22]. (We intentionally gave the wrong label with a probability of 60%, while the correct label with a probability of 40%, to prevent our model to be overconfident.) We also added another loss function on attention matrix [23], which promotes the attention matrix to be diagonal.

4.3. Training Data

To train the above model, we annotated a portion of the words in NEologd. We first roughly classified the words of NEologd as shown in Table 3 using simple regular expressions, excluding some noisy words, such as kanji words written in katakana [8]. The classification was not perfect and we found many misclassifications, but we did not modify them as it was infeasible to correct them manually.

Then, for each category, we sampled the words, the number of which is shown in Table 3 (b). Then the first author of this article is a native speaker of contemporary Tokyo dialect, annotated those words. The author did not know the exact acccents of the most of the extracted words, but entered plausible ones that would sound natural. Some of the yomis of NEologd were wrong, but the author entered plausible accents assuming that these yomis are correct.

In addition to these data, we used 500 sentences, 7,000 UniDic words, and 20,000 synthetic compound words. To synthesize those compound words, we randomly sampled nouns from UniDic, and concatenated them by either of following two rules.

\[
    (1) \ s = s_1[s_2], \ y = y_1|y_2
\]
\[
    (2) \ s = s_1[s_2][\xi|s_3|s_4], \ y = y_1|y_2[y_3|y_4]|y_4
\]

where $'|$ denotes the string concatenation, $\xi$ are randomly drawn from $\eta \in \{\mathrm{no}, \mathrm{ga}, \mathrm{tsu}, \mathrm{wa}\}$, and $\xi \in \{\mathrm{to}, \mathrm{wa}, \mathrm{ga}, \mathrm{no}, \mathrm{mo}\}$, respectively. In either case, we defined the accent using Sagisaka’s rule [9].

We thus obtained nonsense compound words e.g. 海浜しめじ茸 and 朧夜眼 (ka[i]hi[n]shi[j]meji[t]o, [n]saNgau[s]agi).

5. EXPERIMENT

5.1. Accent Estimation Experiment

The experimental setting was as follows. We used 80% of the annotated words for training, and remaining 20% for evaluation. We used the Adam optimizer [24] to train our model; the parameters were $(\alpha, \beta_1, \beta_2, \varepsilon) = (2 \times 10^{-4}, 0.5, 0.9, 10^{-5})$. We applied weight decay of factor $10^{-6}$ (L1 and L2 regularization) after each iteration.
Table 5. Examples of correctly estimated accents. None of these words are found in the training data. Other examples are also shown in Table 4 (The mark ✓ indicates that the top result of MeCab+UniDic analysis of the word is correct.)

| surface | estimated accent | the author’s accent |
|---------|------------------|---------------------|
| 天竺雑 | daigaku | daigaku |
| 信号処理 | shi|n|goshi | shi|n|goshi |
| ケンタウルス座 | ke|n|tarusuza | ke|n|tarusuza |
| ドラム太洗濯座 | do|ramu|shi|kase|ntaku|ka | do|ramu|shi|kase|ntaku|ka |
| 明治神宮 | me|ji|gumi | me|ji|gumi |
| 小竹向原 | kox|takemuk|a|hara | kox|takemuk|a|hara |
| 林桜小杉 | mi|sh|as|hi|ko|sugi | mi|sh|as|hi|ko|sugi |
| 難波北高島 | to|kyo|ootoshi|kyuu|ku | to|kyo|ootoshi|kyuu|ku |
| 紅白折戦旗 | ko|oh|aku|ntta|ga|q|sen | ko|oh|aku|ntta|ga|q|sen |
| 富高三十六 | ful|gaku|sa|n|j|na|r|o|q|kei | ful|gaku|sa|n|j|na|r|o|q|kei |
| ✗ | su|ji | su|ji |
| ((g×w×h×s×o×) | e|gao | e|gao |

The size of mini-batch was 32. We trained our model for 4 days (2.5M steps). The version of UniDic we used was unidic-mecab-kana-accent-2.1.x.

The evaluation criteria were as follows: the exact matching rate (EMR), the rate of the words whose estimated accents exactly matched the ground truths, the average hamming distance (AHD) from the ground truths, the precision TP/(TP + FP) and the recall TP/(TP + FN) of raise “*” and lower “.” Table 4(c) shows the result. Note, considering that some words have several acceptable accents, the actual performance would be a little better than the digits shown in the Table.

From these digits, we can say the following for most categories of the words.

- The proposed method estimated the exact accents of over a half of the words (EMR > 50 %).
- The number of estimation errors in a word is less than 1 on average (AHD < 1).
- We may trust more than 80% of “*” precision > 0.8), and 75% of “.” precision > 0.75.

Table 5 shows the examples of correctly estimated accents. Even when UniDic provided little useful phonetic information about the words (e.g., Python, word2vec, YandexAccess), the proposed method could estimate the accent correctly using the yomis. On the other hand, Table 6 shows the examples of errors. Note, it is sometimes impossible in principle to estimate the accent of some words without taking into account cultural backgrounds or customs. For example, the accents of some place names are customary and difficult to predict even for native speakers unless they are familiar with the neighbourhood. Some of the errors may be of this kind, e.g. Meiji Jingumae, Kotonaka Mikaibara. The estimated accents of these words are possible grammatically, but may sound a little unnatural for local residents.

6. CONCLUDING REMARKS

In this paper, we proposed a neural network-based technique to estimate the accents of Japanese words, using their surfaces and the yomis (phonetic information except the accent). The author annotated 17200 words out of 3 million words listed in NEologd, and trained the model. Experiments showed that the method estimated the accent of some categories of words (e.g. numerals, address, katakana words, etc.) with high accuracies, while the performance was clearly better in 10 cases, UniDic was clearly better in 2 cases, and both were almost evenly evaluated in the remaining 8 cases. Qualitatively, we found our dictionary received lower evaluations in following cases. (1) Even though the estimated accent was correct, the neural TTS system sometimes could not estimate the word correctly, especially when the target word is long (e.g. address, street, numerals, etc.), or the accent pattern is complicated (e.g. more than two accent nuclei “*”). This is possibly due to the mismatch between the training data and the test sentences of TTS. Indeed, those words were rarely used in JSUT corpus. (2) Some research participants did not know the yomis of some difficult words.

7 <https://unidic.ninjal.ac.jp/back_number> 760k words.

8 For example, ‘ju|ugo|fun’, ‘ju|ugo|fun’, ‘ju|ugo|fun’ and ‘ju|ugo|fun’ would all be acceptable pronunciations of the word 十五分.

9 We additionally modified the unigram cost of each word a little, because NEologd’s unigram costs of some categories of words (e.g. person’s name) were too small, in the current version.

10 Female voice, # speaker is 1, approx 10 hours. We resampled all the data from 48kHz to 24kHz.
7. REFERENCES

[1] Y. Kitahara and Z. Uwano, Eds., *Asakura Textbook Series of Japanese Linguistics Vol. 3. Speech and Phonology*, Asakura Publishing, 2003, ISBN 978-4254516432 [in Japanese].

[2] Z. Uwano, “Two-pattern accent systems in three Japanese dialects,” in *Tones and Tunes Volume 1: Typological Studies in Word and Sentence Prosody*, T. Riad and C. Gussenhoven, Eds. 2007, pp. 147–165, Walter de Gruyter.

[3] Y. Den, J. Nakamura, T. Ogiso, and H. Ogura, “A proper approach to Japanese morphological analysis: Dictionary, model, and evaluation,” in *Proc. Language Resource and Evaluation Conference (LREC)*, 2008, pp. 1019–1024.

[4] Y. Den, “A multi-purpose electronic dictionary for morphological analyzers,” *Journal of Japanese Society for Artificial Intelligence*, vol. 24, no. 5, pp. 640–646, 2009, [in Japanese].

[5] Y. Den, A. Yamada, H. Ogura, H. Koiso, and T. Ogiso, *UniDic version 1.3.9 Users Manual*, [in Japanese].

[6] T. Kudo, K. Yamamoto, and Y. Matsumoto, “Applying conditional random fields to Japanese morphological analysis,” in *Proc. EMNLP*, 2004, pp. 230–237.

[7] T. Sato, T. Hashimoto, and M. Okumura, “Operation of a word segmentation dictionary generation system called NEologd,” in *IPSJ-SIGNL*, 2016, pp. NL–229–15, Information Processing Society of Japan, [in Japanese].

[8] T. Sato, T. Hashimoto, and M. Okumura, “Implementation of a word segmentation dictionary called mecab-ipadic-NEologd and study on how to use it effectively for information retrieval,” in *Proc. 23rd Annual Meeting of the Association for NLP*, 2017, pp. NLP2017–B6–1, [in Japanese].

[9] Y. Sagisaka and H. Sato, “Accentuation rules for Japanese word concatenation,” *IEICE Trans. Inf. & Sys.*, vol. J66-D, no. 7, pp. 849–856, 1983, [in Japanese].

[10] M. Miyazaki, “Reading rules of numerals for a Japanese text to speech system,” *IPSJ Journal*, vol. 25, no. 6, pp. 1035–1043, 1984, [in Japanese].

[11] R. Kita, N. Minematsu, and K. Hirose, “Development of rules of word accent sandhi and their improvement for Japanese TTS systems,” in *IEICE technical report, SP.*, 2002, vol. 102, pp. 13–18, [in Japanese].

[12] S. Kawamoto, H. Shimodaira, T. Nitta, T. Nishimoto, S. Nakamura, K. Itou, S. Morishima, T. Yotsukura, A. Kai, A. Lee, Y. Yamashita, T. Kobayashi, K. Tokuda, K. Hirose, N. Minematsu, A. Yamada, Y. Den, T. Utsuro, and S. Sagayama, “Galatea: Open-source software for developing anthropomorphic spoken dialog agents,” in *Life-Like Characters: Tools, Affective Functions, and Applications*, Helmut Prendinger and Mitsuru Ishizuka, Eds., Berlin, Heidelberg, 2004, pp. 187–211, Springer Berlin Heidelberg.

[13] S. Fukayama, K. Nakatsuma, S. Sako, T. Nishimoto, and S. Sagayama, “Automatic song composition from the lyrics exploiting prosody of the Japanese language,” in *Proc. Sound and Music Computing Conference (SMC)*, 2010, pp. 299–302.

[14] T. Nagano, S. Mori, and M. Nishimura, “A stochastic approach to phoneme and accent estimation,” in *Proc. INTERSPEECH*, 2005, pp. 3293–3296.

[15] N. Minematsu, S. Kobayashi, S. Shimizu, and K. Hirose, “Improved prediction of Japanese word accent sandhi using CRF,” in *Proc. INTERSPEECH*, 2012, pp. 2562–2565.

[16] M. Suzuki, R. Kuroiwa, K. Innami, S. Kobayashi, S. Shimizu, N. Minematsu, and K. Hirose, “Accent sandhi estimation of Tokyo dialect of Japanese using conditional random fields,” *IEICE Trans. Info. & Sys.*, vol. 100, pp. 655–661, 2017.

[17] A. Bruguier, H. Zen, and A. Arkhangorodsky, “Sequence-to-sequence neural network model with 2D attention for learning Japanese pitch accents,” in *Proc. INTERSPEECH*, 2018, pp. 1284–1287.

[18] M.-T. Luong, H. Pham, and C. D. Manning, “Effective approaches to attention-based neural machine translation,” in *Proc. EMNLP*, 2015, pp. 1412–1421, arXiv:1508.04025.

[19] S. Ioffe, “Batch renormalization: Towards reducing minibatch dependence in batch-normalized models,” *NIPS*, pp. 1945–1953, 2017.

[20] R. K. Srivastava, K. Greff, and J. Schmidhuber, “Training very deep networks,” *NIPS*, pp. 2377–2385, 2015, arXiv:1507.06228.

[21] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” in *Proc. CVPR*, 2016, pp. 2818–2826.

[22] R. Müller, S. Kornblith, and G. Hinton, “When does label smoothing help?,” *NeurIPS*, 2019, arXiv:1906.02629.

[23] H. Tachibana, K. Uenoyama, and S. Aihara, “Efficiently trainable text-to-speech system based on deep convolutional networks with guided attention,” in *Proc. ICASSP*, 2018, pp. 4784–4788, arXiv:1710.08969.

[24] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in *Proc. ICLR 2015*, 2014, arXiv:1412.6980.

[25] R. Sonobe, S. Takamichi, and H. Saruwatari, “JSUT corpus: free large-scale Japanese speech corpus for end-to-end speech synthesis,” 2017, arXiv:1711.00354.
Supplementary Material

Update Sep., 2020.

Trained Model and Source Code
The trained model and the inference code (automatic dictionary generator) are available at the following site.

https://github.com/PKSHATechnology-Research/tdmelodic