Developing and validating automatic annotation system of silent pause locations and disfluency words

Fluency

Ryuki Matsuura | Waseda University | Location: Mezzanine, Time: 1:30 p.m. – 3:00 p.m., Date: Thursday, June 8, 2023

Highlight

1) **The substantial agreement** between automatic and manual annotation (pause locations: *κ=.613* / disfluency words: *κ=.674*).
2) **Moderate-to-strong correlations** between automatically and manually calculated fluency measures (*r*=|*.444 - .868*|).
3) Automatic fluency measures have **high predictability of human judgement fluency** (*R2=.726*).

1. Introduction

Why automatic annotation of fluency?

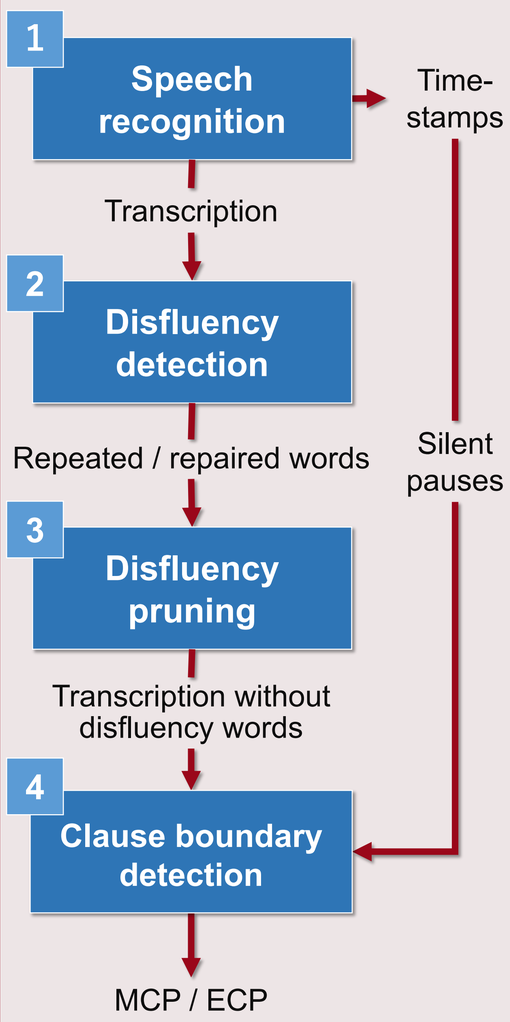
- *For researchers*. The **labour intensiveness** of manually annotating temporal features of speech (e.g., pause & hesitation).
- *For testers*. The potential for **automated scoring of L2 speech** as fluency is robust indicator of L2 oral proficiency (Tavakoli et al., 2020) (e.g., Chen et al., 2018; Saeki et al., 2021; Saito et al., 2022).

Any challenges?

- **Automatic fluency annotation systems** have thus been developed (de Jong & Wempe 2009; de Jong et al., 2021).
- The automatic methods **are a valid alternative** to manual annotation (Suzuki et al., 2021).
- Existing systems **cannot annotate** following features despite their predictive power for fluency judgement (Kahng, 2018; Suzuki et al., 2021)
  1. **Mid- or end-clause pause (MCP / ECP) distinction** (i.e., silent pauses within a clause or between clauses)
  2. **Disfluency words** (e.g., self-repair, repetition & false start)

The current study aims to develop an annotation system which can annotate silent pause locations and disfluency words.

2. Automatic annotation design



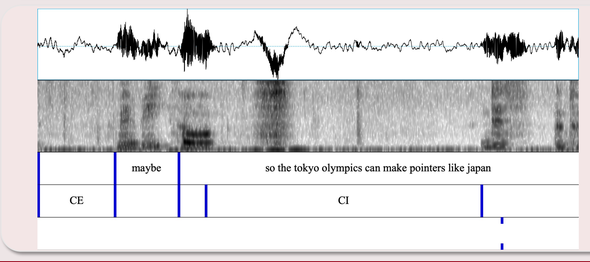
1) Speech recognition system by Rev.ai[1] (*WER=27.3%*) predicts
   - Time-aligned word sequence
   - Silent pauses (from the timestamps)

1. https://www.rev.ai/async

2) Using NLP technology, BERT (Devlin et al., 2019), repeated / repaired words are detected from transcript.

3) The detected disfluency words are removed.

4) Using a dependency parser
   1. Clause boundaries are detected.
   2. Silent pauses are classified as MCP / ECP.



3. Method

Aims

1. To test **accuracy of automatic annotation** of the silent pause locations and disfluency words.
2. To evaluate **the predictive validity of automatically calculated fluency measures** in terms of
   a. Correlation with corresponding manual measures
   b. Explained variance of listener-based judgements of fluency.

Dataset

1. Dialogue speech by Japanese English learners (*N=85*; N_{turn}*=2,236)* (Saeki et al., 2022).
   - Two research assistants manually annotated for silent pause locations and disfluency words.
2. Monologue speech by Japanese English learners (*N=512*) (Suzuki & Kormos, 2021).
   - Two PhD students in Applied Linguistics evaluated for fluency using a 9-point scale.

Fluency Measures

- Speed measures : Articulation rate (AR)
- Breakdown measures : MCP/ECP ratio, MCP/ECP duration
- Repair measures : Disfluency ratio (DR)

4. Result

1. There is **the substantial agreement between automatic and manual annotations**.

Table 1. Cohen's κ between automatic and manual annotation

	Silent pause locations	Disfluency words
Agreement (Cohen's κ)	**0.613**	**0.674**

2. Automatically calculated fluency measures have (Table 2 & 3)
   a. **moderate-to-strong correlations with manual ones**
   b. **high predictability of fluency judgements.**

Table 2. Correlation coefficients between automatic and manual measures

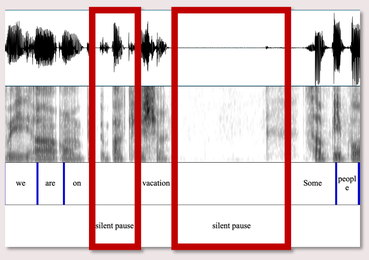
	AR	MCP ratio	ECP ratio	MCP duration	ECP duration	DR
Correlation (Pearson's r)	**0.444**	**0.665**	**0.537**	**0.868**	**0.493**	**0.620**

Table 3. R2 scores of a regression model predicting fluency judgements

	Manual	Praat script (de Jong et al., 2021)	Proposed
Predictability (R2 score)	**0.644**	**0.435**	**0.726**

5. Discussion

- The annotation system has **the substantial agreement** (*κ=.613 / .674*) and **the predictive power of the fluency judgements outperformed** the conventional one (*R2=.726 vs. .435*).
  - The automatic annotation of pause locations and disfluency words is important for the automatic assessment system (cf., Suzuki et al., 2021).
- **The correlation between automatic and manual measures for AR and ECP duration were relatively low** (*r=.444 / .493*).
- **R2 score of the fluency judgement prediction based on the proposed annotation is "higher" than manual one** (*R2=.726* vs. *.644*).
  - Fluency measures might have negatively biased towards lower-proficiency level learners due to low speech recognition accuracy, and which in turn exaggerated the R2 value (cf., Tan et al., 2014).



Acknowledgements

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Chen, L., Zechner, K., Yoon, S.-Y., Evanini, K., Wang, X., Loukina, A., Tao, J., Davis, L., Lee, C.M., Ma, M., Mundkowsky, R., Lu, C., Leong, C.W. and Gyawali, B. (2018), Automated Scoring of Nonnative Speech Using the SpeechRaterSM v. 5.0 Engine. ETS Research Report Series, 2018: 1-31.

de Jong, N. H., & Wempe, T. (2009). Praat script to detect syllable nuclei and measure speech rate automatically. *Behavior Research Methods*, 41(2), 385–390.

de Jong, N. H., Pacilly, J. and Heeren W. (2021). PRAAT scripts to measure speed fluency and breakdown fluency in speech automatically. Assessment in Education: Principles, Policy and Practice, 28(4), 456–476.

Kahng, J. (2018). The effect of pause location on perceived fluency. *Applied Psycholinguistics*, 39(3), 569–591.

Saeki, M., Matsuyama, Y., Kobashikawa, S., Ogawa, T. and Kobayashi, T. (2021). Analysis of Multimodal Features for Speaking Proficiency Scoring in an Interview Dialogue. *2021 IEEE Spoken Language Technology Workshop (SLT)*, 629-635.

Saeki, M., Demkow, W., Kobayashi, T. and Matsuyama, Y. (2022). A WoZ Study for an Incremental Proficiency Scoring Interview Agent Eliciting Ratable Samples. *Conversational AI for Natural Human-Centric Interaction. Lecture Notes in Electrical Engineering*, 943, 193-201.

Saito, K., Macmillan, K., Kachlicka, M., Kunihara, T., & Minematsu, N. (2022). Automated assessment of second language comprehensibility: Review, training, validation, and generalization studies. *Studies in Second Language Acquisition*, 1–30.

Suzuki, S., Kormos, J. and Uchihara, T. (2021). The Relationship Between Utterance and Perceived Fluency: A Meta-Analysis of Correlational Studies. *The Modern language Journal*, 105(2), 435-463.

Suzuki, S. and Kormos, J. (2022). The Multidimensionality of Second Language Oral Fluency: Interfacing Cognitive Fluency and Utterance Fluency. *Studies in Second Language Acquisition*, 45(1), 38-64.

Tao, J., Evanini, K. and Wang, X. (2014). The influence of automatic speech recognition accuracy on the performance of an automated speech assessment system. *2014 IEEE Spoken Language Technology Workshop (SLT)*, 294–299.

Tavakoli, P., Nakatsuhara, F. and Hunter, A. (2020). Aspects of Fluency Across Assessed Levels of Speaking Proficiency. *Modern Language Journal*, 104(1), 169–191.