COMPARISON OF SPEAKER ROLE RECOGNITION AND SPEAKER ENROLLMENT PROTOCOL FOR CONVERSATIONAL CLINICAL INTERVIEWS

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ABSTRACT

Conversations between a clinician and a patient, in natural conditions, are valuable sources of information for medical follow-up. The automatic analysis of these dialogues could help extract new language markers and speed-up the clinicians’ reports. Yet, it is not clear which speech processing pipeline is the most performing to detect and identify the speaker turns, especially for individuals with speech and language disorders. Here, we proposed a split of the data that allows conducting a comparative evaluation of speaker role recognition and speaker enrollment methods to solve this task. We trained end-to-end neural network architectures to adapt to each task and evaluate each approach under the same metric. Experimental results are reported on naturalistic clinical conversations between Neuropsychologist and Interviewees, at different stages of Huntington’s disease. We found that our Speaker Role Recognition model gave the best performances. In addition, our study underlined the importance of retraining models with in-domain data. Finally, we observed that results do not depend on the demographics of the Interviewee, highlighting the clinical relevance of our methods.

Index Terms— Clinical Interviews, Speaker Role Recognition, Speaker Enrollment, Pathological Speech Processing, Huntington’s Disease.

1. INTRODUCTION

During the last decades, it became easier to collect large naturalistic corpora of speech data. It is now possible to obtain new realistic measurements of turn-takings and linguistic behaviors [1]. These measurements can be especially useful during clinical interviews as they augment the current clinical panel of assessments and unlock home-based assessments [2]. The remote automatic measure of symptoms of patients with Neurodegenerative diseases could greatly improve the follow-up of patients and speed-up ongoing clinical trials.

Yet, this methodology relies on the heavy burden of manual annotation to reach the necessary amount needed to draw significant conclusions. It is now indispensable to have robust speech processing pipelines to extract meaningful insights from these long naturalistic datasets. Huntington’s Disease represents a unique opportunity to design and test these speech algorithms for Neurodegenerative diseases. Indeed, individuals with the Huntington’s disease can exhibit a large spectrum of speech and language symptoms [3] and it is possible to follow gene carriers even before the official clinical onset of the disease [4]. The first unavoidable computational tasks to extract speech and linguistic information from medical interviews are: (1) the detection of speaker-homogeneous portions of voice activity [5] and (2) the identification of the speaker [6]. Speaker Turns are clinically informative for the diagnostic in Huntington’s Disease [7, 3].

First, a number of studies are trying to solve this problem directly from the audio signal and linguistic outputs, also referred to as Speaker Role Recognition. They are taking advantage of the specificities (ex: prosody, specific vocabulary,
adapted language models) of each role in the different domains: Broadcast news programs [6], Meetings [8], Medical conversations [9], Child-centered recordings [10].

Another approach relies on Speaker Enrollment [11, 12], it aims to check the identity of a given speech segment based on an enrolled speaker template. Our study differ from these studies as they are evaluating their pipelines with already segmented speaker-homogeneous speech segments. Another related approach is the Personal VAD (Voice Activity Detection) model from [13] where they used an enrolled speaker template to detect speech segments from each individual speaker, on the Librispeech Dataset.

None of these approaches have been compared under the same evaluation metric, despite prior works aiming at solving both these tasks [14] and their high degree of similarities.

Here in this paper, we aimed to detect automatically the portions of speech and to identify the speakers in medical conversation between Neuropsychologists and Interviewees. These interviewees are either Healthy Controls (C), gene carriers without overt manifestation of Huntington’s Disease (preHD) and manifest gene carriers of Huntington’s Disease (HD). We used two different speech processing approaches to deal with these 2 problems (Figure 1): Speaker Role Recognition and Speaker Enrollment Protocol.

2. DATA, EVALUATION SPLITS, METRICS

2.1. Dataset

Ninety four participants were included from two observational cohorts (NCT01412125 and NCT03119246) in this ancillary study at the Hospital Henri-Mondor Créteil, France: 72 people tested with a number of CAG repeats on the Huntington gene above 35 \( \text{CAG} > 35 \) (CAG > 35), and 22 Healthy Controls (C), Mutant Huntington gene carriers were considered premanifest if they both score less than five at the Total Motor score (TMS) and their Total functional capacity (TFC) equals 13 [16] using the Unified Huntington Disease Rating Scale (UHDRS) [17]. The demographics are summarized in Table 1. All participants signed an informed consent and conducted an interview with an expert neuropsychologist. Therefore in the current setting, there are two roles in each conversational interview: a Neuropsychologist and an Interviewee. The speech data were annotated with Seshat [18] and Praat [19] softwares. The annotators were second-year graduate students in speech pathology, all French native speakers. The recordings were done in the same condition for all participants, with a ZOOM H4n Pro recorder, sampled at 44.1 kHz with a 16-bit resolution.

2.2. Splits of the data

The dataset is composed of \( K = 94 \) interviews \( \mathcal{I}_1, \ldots, \mathcal{I}_K \). We designed a split of the dataset to compare the Speaker Role Recognition and Speaker Enrollment pipelines (See Figure 2). The dataset is split in three sets which we refer to meta-train set \( M_{\text{train}} \), meta-dev set \( M_{\text{dev}} \) and meta-test set \( M_{\text{test}} \) with the ratio of 60%, 20%, and 20%, respectively. Interview \( I \in \mathcal{I}_1, \ldots, \mathcal{I}_K \) is composed of \( N_I \) segments \( I = \{U_0, U_2, \ldots, U_{N_I}\} \). Each segment \( U_i \) is pronounced by a speaker \( s_i \). We summarized the corpus statistics in the Table 2.

Each interview \( I \) in the meta-dev and meta-test is split in two sets which we refer dev set \( X_{\text{dev}} \) and test set \( X_{\text{test}} \). \( X_{\text{test}} \) is always kept fixed through all experiments, and we study the influence of the size of the \( X_{\text{dev}} \) based on \( T_{\text{dev}} \) that filters the segments (cf Figure 2).

All the data from the meta-train set \( M_{\text{train}} \) is used to train or fine-tune the neural network models for voice activity detection, speaker change detection, speaker role recognition, and speaker enrollment. The dev set \( X_{\text{dev}} \) of the meta-dev set \( M_{\text{dev}} \) and the dev set \( X_{\text{dev}} \) of the meta-test set \( M_{\text{test}} \) are only used for the speaker enrollment experiments, to build the template representation of each speakers. The results on the test set \( X_{\text{test}} \) of the meta-dev set \( M_{\text{dev}} \) are used to select all the hyper-parameters and select the best model for each experiment. The final comparison is done with the test set \( X_{\text{test}} \) of the meta-test set \( M_{\text{test}} \).

![Figure 2: Illustration of the data split with 4 interviews. Each line \( I_i \) represents an interview between the Interviewee and the Neuropsychologist. The elevation of each row indicates 'who speaks when'. The segments can overlap.](image)

2.3. Metrics

To compare the final performance of the pipeline systems, we use the Identification Error Rate (IER) taking into account both the segmentation errors and confusion errors. We obtained the IER with `pyannote.metrics` [21].

\[
\text{IER} = \frac{T_{\text{false alarm}} + T_{\text{missed detection}} + T_{\text{confusion}}}{T_{\text{Total}}}
\]
The T_{\text{norm}} value in the IER is related to the Missclassification Rate (MR%) used in Speaker Role Recognition study [22], which is based on Frames and not duration of the turns. We compared the different approaches as a function of the size of the enrollment T_{\text{dev}} in Figure 3. Regarding the relevance for Healthcare applications, we showed the IER details in Figure 4 for both best approaches based on the Interviewee demographics.

3. METHODS

3.1. Speaker Role Recognition

We used a modified approach from [10] for the Speaker Role Recognition. We trained on M_{\text{train}} a unique model to detect each role (Neuropsychologist, Interviewee), and selects the best epoch on M_{\text{dev}}. This is a multi-label multi-class segmentation problem. A threshold parameter for each role is optimized on the Meta-dev M_{\text{dev}}. The SCD task is modeled as an audio sequence labeling task. There are 2 classes (Speech or Non-Speech). The VAD labels for each interview I are the presence or not of a segment U_i at time t.

The model can be used already Pretrained or Retrained on the meta-train set M_{\text{train}} of our dataset. We choose the DIHARD dataset [25] as a potential pretrained dataset as it contains multiple source domain data (clinical interviews among them). When trained from scratch, the training is done for 200 pyannote epochs and the model is selected on the Meta-dev. The SCL model is also composed of SincNet filters with 2 bi-recurrent LSTM layers and 2 feed-forward layers. The full specifications can be found here.

3.2. Speaker Change Detection

The second step is the Speaker Change Detection (SCD), i.e. obtain the moment when one of a speaker starts or stops talking. It can also be modeled as an audio sequence labeling task. There are 2 classes (Change or No-Change). The SCD labels for each interview I are the start or end of a segment U_i at time t. We also compared Pretrained on DIHARD and Retrained models. We used the same model as for the Voice Activity Detection. The full specifications can be found here.

Based on VAD and SCD outputs, we can now obtain for each Interview I a set of N_i candidates speaker-homogeneous segments \{U_1, ..., U_{N_i}\}.

3.2.4. Identification

3.2.1. Voice Activity Detection

The first step is the Voice Activity Detection (VAD), i.e. obtain the speech segments in the audio signal. It can be modeled as an audio sequence labeling task. There are 2 classes (Speech or Non-Speech). The VAD labels for each interview I are the presence or not of a segment U_i at time t.

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3.2.4. Identification

For the identification stage, we use the function f_\theta and the different representation m_j of the speakers from the enrollment stage. We used the following cosine distance D to build a scoring function and compare each segment

\[ m_j = \frac{1}{|U_{\text{enrollment speaker } j}|} \sum_{U \in U_{\text{enrollment speaker } j}} f_\theta(U) \]
Fig. 3. Identification Error Rates for the different combination of approaches on the test set $X_{test}$ of the meta-test set $M_{test}$ as a function of the size of the enrollment parameter $T_{dev}$. Spk Emb., VAD, SCD stand for Speaker Embedding, Voice Activity Detection and Speaker Change Detection. Best performance of each approach displayed at the best $T_{dev}$.

$\hat{U} \in \{\hat{U}_1, \ldots, \hat{U}_{N_I}\}$ to each template $m_j$.

$$D(\hat{U}, m_j) = \frac{1}{2} \left( 1 - \frac{f_\theta(\hat{U})^T m_j}{||f_\theta(\hat{U})|| \cdot ||m_j||} \right)$$ (2)

$$\text{argmin}_j D(\hat{U}, m_j) : \text{Selects Speaker } j$$ (3)

In addition, we analyzed topline performance of the speaker embedding models when the Ground Truth Segmentation is provided. Finally, we computed a chance baseline based on speaker Enrollment by randomly permutating all the cosine distances.

4. RESULTS AND DISCUSSIONS

Figure 3 shows results in term of IER for the different approaches. Both approaches greatly improved over chance. If we consider pipelines solving both segmentation and identification, our best performance is obtained using the Speaker Role Recognition approach with IER=19.5% while the Speaker Enrollment Protocol obtained at best IER=23.6% at $T_{dev} = 120s$, with Retrained VAD/SCD models and Finetuned Speaker Embedding. Even though, the Speaker Enrollment protocol has per-speaker templates, it is not surpassing the Speaker Role Recognition approach. The topline with Ground Truth Segmentation (IER=9.1%) indicated that Speaker Enrollment could benefit greatly from a better detection of speaker-homogeneous turns. Errors of Speaker Enrollment are accumulated through the steps and can not be recovered, while Speaker Role Recognition might take advantage of solving all steps together in its end-to-end approach.

Increasing the size of the Template Enrollment $m_j$ for each speaker with $T_{dev}$ lead to light improvements to all Speaker Enrollment methods. The finetuning of the X-vector speaker embedding model with in-domain is especially crucial (ex: Based on retrained VAD/SCD the IER decreases from 28.2% to 23.6%). An additional ablation study on the size of the meta-training set $M_{train}$ showed us that the IER goes from IER=19.5% to IER=26.5% for the Speaker Role Recognition model trained with only 10% of $M_{train}$. In Figure 4, we showed the IER, for both approaches, along with the Interviewees’ demographics. The IER is not collapsing for any of the group and for both methods, even for the Control which don’t suffer from any speech disorder.

5. CONCLUSION AND FUTURE WORK

Detection and Identification of speaker turns are fundamental problems in speech processing, especially in healthcare applications. While works studying these problems in isolation has provided valuable insights, in this work, we showed that Speaker Role Recognition was the most suitable approach for Interviewees at different stages of Huntington’s Disease. Lastly, we observed that both approaches have the potential to be used for clinical diagnosis. For future work, we plan to investigate the use of these methods to derive biomarkers automatically and compare them to classic approaches [27] and extend it to recordings with a variable number of speakers.

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7. REFERENCES

[1] Sharon Ash and Murray Grossman, “Why study connected speech production,” *Cognitive neuroscience of natural language use*, pp. 29–58, 2015.

[2] Katie Matton, Melvin G McInnis, and Emily Mower Provost, “Into the wild: Transitioning from recognizing mood in clinical interactions to personal conversations for individuals with bipolar disorder,” *Proc. Interspeech*, pp. 1438–1442, 2019.

[3] Adam P Vogel, Christopher Shirbin, Andrew J Churchyard, and Julie C Stout, “Speech acoustic markers of early stage and prodromal huntington’s disease: a marker of disease onset?,” *Neuropsychologia*, vol. 50, no. 14, pp. 3273–3278, 2012.

[4] Wolfram Hinzen, Joana Rosselló, Catí Morey, Estela Camara, Clara García-Gorro, Raymond Salvador, and Ruth de Diego-Balaguer, “A systematic linguistic profile of spontaneous narrative speech in pre-symptomatic and early stage huntington’s disease,” *Cortex*, vol. 100, pp. 71–83, 2018.

[5] Simon Graf, Tobias Herbrig, Markus Buck, and Gerhard Schmidt, “Features for voice activity detection: a comparative analysis,” *EURASIP Journal on Advances in Signal Processing*, vol. 2015, no. 1, pp. 91, 2015.

[6] Benjamin Bigot, Julien Pinquier, Isabelle Ferrané, and Régine André-Obrecht, “Looking for relevant features for speaker role recognition,” in *Eleventh Annual Conference of the International Speech Communication Association*, 2010.

[7] Matthew Perez, Wenyu Jin, Duc Le, Noelle Carlozzi, Praveen Dayalu, Angela Roberts, and Emily Mower Provost, “Classification of huntington disease using acoustic and lexical features,” in *INTERSPEECH*, 2018, vol. 2018, pp. 1898–1902.

[8] Ashutosh Sapru and Fabio Valente, “Automatic speaker role labeling in ami meetings: recognition of formal and social roles,” in *ICASSP*. IEEE, 2012, pp. 5057–5060.

[9] Nikolaos Flemotomos, Pavlos Papadopoulos, James Gibson, and Shrikanth Narayanan, “Combined speaker clustering and role recognition in conversational speech,” *Proc. Interspeech 2018*, pp. 1378–1382, 2018.

[10] Marvin Lavechin, Ruben Bousbib, Hervé Bredin, Emmanuel Dupoux, and Alejandrina Cristia, “An open-source voice type classifier for child-centered daylong recordings,” *arXiv preprint arXiv:2005.12656*, 2020.

[11] David Snyder, Daniel Garcia-Romero, Daniel Povey, and Sanjeev Khudanpur, “Deep neural network embeddings for text-independent speaker verification,” *Proc. Interspeech*, pp. 999–1003, 2017.

[12] Georg Heigold, Ignacio Moreno, Samy Bengio, and Noam Shazeer, “End-to-end text-dependent speaker verification,” in *ICASSP*. IEEE, 2016, pp. 5115–5119.

[13] Shaojin Ding, Quan Wang, Shuo-Yin Chang, Li Wan, and Ignacio-Lopez Moreno, “Personal vad: Speaker-conditioned voice activity detection,” in *Proc. Odyssey 2020 The Speaker and Language Recognition Workshop*, 2020, pp. 433–439.

[14] Paola García, Jesús Villalba, Hervé Bredin, Jun Du, Diego Cสถาน, Alejandrina Cristia, Latane Bullock, Ling Guo, Koji Okabe, Phani Sankar Nidadavolu, et al., “Speaker detection in the wild: Lessons learned from jsalt 2019,” 2019.

[15] James F Gusella, Nancy S Wexler, P Michael Conneally, Susan L Naylor, Mary Anne Anderson, Rudolph E Tanzi, Paul C Watkins, Kathleen Ottina, Margaret R Wallace, Alan Y Sakaguchi, et al., “A polymorphic dna marker genetically linked to huntington’s disease,” *Nature*, vol. 306, no. 5940, pp. 234–238, 1983.

[16] Sarah J Tabrizi, Douglas R Langbehn, Blair R Leavitt, Raymond AC Roos, Alexandra Durr, David Craufurd, Christopher Kennard, Stephen L Hicks, Nick C Fox, Rachael I Scahi, et al., “Biological and clinical manifestations of huntington’s disease in the longitudinal track-hd study: cross-sectional analysis of baseline data,” *The Lancet Neurology*, vol. 8, no. 9, pp. 791–801, 2009.

[17] Karl Kieburz, John B Penney, Peter Corno, Neal Ranen, Ira Shoulson, Andrew Feigin, Davi Abwender, J Timothy Greenamyre, Donald Higgins, Frederick J Marshall, et al., “Unified huntington’s disease rating scale: reliability and consistency,” *Neurology*, vol. 11, no. 2, pp. 136–142, 2001.

[18] Hadrien Titeux*, Rachid Riad*, Xuan-Nga Cao, Nicolas Hamilakis, Kris Madden, Alejandrina Cristia, Anne-Catherine Bachoud-Lévi, and Emmanuel Dupoux, “Seshat: A tool for managing and verifying annotation campaigns of audio data,” in *LREC*, Marseille, May 2020, *Equal contribution.*

[19] Paul Boersma et al., “Praat, a system for doing phonetics by computer,” *Glott international*, vol. 5, 2002.

[20] Ira Shoulson, “Huntington disease: functional capacities in patients treated with neuroleptic and antidepressant drugs,” *Neurology*, vol. 31, no. 10, pp. 1333–1333, 1981.

[21] Hervé Bredin, “pyannote.metrics: a toolkit for reproducible evaluation, diagnostic, and error analysis of speaker diarization systems,” in *Interspeech*, Stockholm, Sweden, August 2017.

[22] Nikolaos Flemotomos, Panayiotis Georgiou, David C Atkins, and Shrikanth Narayanan, “Role specific lattice rescoring for speaker role recognition from speech recognition outputs,” in *ICASSP*. IEEE, 2019, pp. 7330–7334.

[23] Mirco Ravanelli and Yoshua Bengio, “Speaker recognition from raw waveform with sincnet,” in *Spoken Language Technology Workshop (SLT)*. IEEE, 2018, pp. 1021–1028.

[24] Hervé Bredin, Ruiqing Yin, Juan Manuel Coria, Gregory Gelly, Pavel Korshunov, Marvin Lavechin, Diego Fustes, Hadrien Titeux, Wassim Bouaziz, and Marie-Philippe Gill, “Pyannote. audio: neural building blocks for speaker diarization,” in *ICASSP*. IEEE, 2020, pp. 7124–7128.

[25] Neville Ryant, Kenneth Church, Christopher Cieri, Alejandrina Cristia, Jun Du, Sriman Ganapathy, and Mark Liberman, “The second dihard diarization challenge: Dataset, task, and baselines,” *Proc. Interspeech*, pp. 978–982, 2019.

[26] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Voxceleb: a large-scale speaker identification dataset,” *Telephony*, vol. 3, pp. 33–039, 2017.

[27] Rachid Riad, Hadrien Titeux, Laurie Lemoine, Justine Monbel, Jennifer Hamet Bagnou, Xuan Nga Cao, Emmanuel Dupoux, and Anne-Catherine Bachoud-Lévi, “Vocal markers from sustained phonation in huntington’s disease,” *arXiv preprint arXiv:2006.05365*, 2020.
8. APPENDIX

Readers can find details of Inter-annotator agreements in [18] where we measured the agreements to annotate speaker turns in these medical conversations between Interviewees.

8.1. Ablation study

Table 3. Speaker Role Recognition Ablation study: Identification Error Rates on the test set $X_{test}$ of the meta-test set $M_{test}$ as a function of the percentage of interview in the meta-train set $M_{train}$. MD stands for Missed detection, FA for False Alarm and Conf. for Confusion.

| Percentage of $M_{train}$ | MD   | FA    | Conf. | IER  |
|---------------------------|------|-------|-------|------|
| 10%                       | 8.0  | 14.5  | 3.9   | 26.5 |
| 20%                       | 7.8  | 12.4  | 3.8   | 24.0 |
| 50%                       | 7.5  | 10.4  | 2.5   | 20.7 |
| 100%                      | 7.1  | 10.2  | 2.3   | 19.5 |

We ran an ablation study (Table 3) for the Speaker Role Recognition to measure the amount of data necessary. Even though models are better than Chance, we found out that at least 50% of our dataset (28 Interviews) is necessary to outperform the Speaker Enrollment Protocol pipeline (20.7% vs 23.6%).

The details of the IER showed that the most important component is the False Alarm (FA), and the increase of size allowed to gain 4 points of FA.

8.2. Clinical Relevance: Speech Markers

In previous studies in Huntington’s Disease [3, 7], the Ratio of Silence and Statistics on utterances and were informative to distinguish between classes of Individuals. These speech markers can be extracted directly from the prediction of the Speaker Role Recognition outputs. We computed the Ratio of Silence and the Standard Deviation of Duration of Utterances on the test set of the Meta-test set $M_{test}$. This computation was done both from the Ground Truth Segmentation and the segmentation provided by the Speaker role recognition system, see Figure 5 and Figure 6.

We found that the automatic system outputs behaved differently based on each speech marker. The Ratio of Silence was better predicted than the SD of Duration of Utterances. Some bias of the predictive system might not hurt the IER metric but hurt the reliability of some measures. Fortunately, the automatic system does not seem to have bias per class.

In future work, it would be valuable to take into account the speech markers in the loss and validation of the system.

Fig. 5. Comparison of the Ratio of Silence between the Ground truth segmentation and the best Speaker role recognition pipeline. The comparison is done on the test sets $X_{test}$ of the Meta-test set $M_{test}$.

Fig. 6. Comparison of the Standard Deviations (SD) of the Duration of Utterances of Interviewees between the Ground truth segmentation and the best Speaker role recognition system. The comparison is done on the test sets $X_{test}$ of the Meta-test set $M_{test}$.