AN ANALYSIS OF DEGENERATING SPEECH DUE TO PROGRESSIVE DYSARTHRIA ON ASR PERFORMANCE

Katrin Tomanek1, Katie Seaver2, Pan-Pan Jiang1, Richard Cave3, Lauren Harrell1, Jordan R. Green2

1Google LLC, 2MGH Institute of Health Professions, 3Language and Cognition, UCL
kattrintomanek@google.com, jgreen2@mghihp.edu

ABSTRACT

Although personalized automatic speech recognition (ASR) models have recently been improved to recognize even severely impaired speech, model performance may degrade over time for persons with degenerating speech. The aims of this study were to (1) analyze the change of performance of ASR over time in individuals with degrading speech, and (2) explore mitigation strategies to optimize recognition throughout disease progression. Speech was recorded by four individuals with degrading speech due to amyotrophic lateral sclerosis (ALS). Word error rates (WER) across recording sessions were computed for three ASR models: Unadapted Speaker Independent (U-SI), Adapted Speaker Independent (A-SI), and Adapted Speaker Dependent (A-SD or personalized). The performance of all models degraded significantly over time as speech became more impaired, but the A-SD model improved markedly when updated with recordings from the severe stages of speech progression. Recording additional utterances early in the disease before significant speech degradation did not improve the performance of A-SD models. This emphasizes the importance of continuous recording (and model retraining) when providing personalized models for individuals with progressive speech impairments.

1. INTRODUCTION

Amyotrophic lateral sclerosis (ALS), also known as motor neuron disease is a progressive, ultimately fatal disease causing progressive loss of motor function [1]. ALS progression is heterogeneous in terms of the pattern of spread across body parts and the rate of functional decline [2]. Between 80-95% of people living with ALS (PALS) experience progressive dysarthria and increasing difficulty communicating daily needs via speech [3]. Speech decline is fastest for individuals first presenting symptoms in the head and neck muscles [4, 5] and dysarthria can progress rapidly, rendering speech unusable within 23 months from diagnosis [4].

Automatic speech recognition (ASR) may significantly extend functional communication in PALS [6]. However, the speech of PALS is challenging to recognize due to progressing dysarthria [7]. Dysarthria due to ALS is characterized by spectral and temporal alterations to the speech signal resulting in prolonged, distorted, and less distinct phonemes [8], increased nasal resonances [9], decreased vocal harmonics [10], and increased duration and frequency of pauses [11].

Recent work shows that ASR systems trained on typical speech poorly generalize to dysarthric speech [12]. In contrast, personalized models trained using samples from the end-user speaker, can be highly accurate - even for severe dysarthria [2, 13, 14] under some speaking conditions (i.e., short, prompted phrases) and with limited amount of data to personalize on [15]. However the performance of these models is likely to degrade over time in PALS as speech becomes slower and less intelligible. Little is known about the tolerance of personalized ASR models to progressive speech changes, and when models need to be updated to optimize accuracy. Specialized training strategies and recording schedules may be needed to boost performance during advanced disease progression. Performance might be enhanced by using recordings collected during the early stage of progression for training. For this study, we identified four speakers from the Euphonia Corpus [16] where patterns of degenerating speech could be observed. We then analyzed how speaker independent and speaker dependent ASR models degrade over time as a function of speech severity, and explored strategies to improve personalized models over the course of progression with limited amounts of new data.

2. METHODS

Subjects and speech recordings. Four subjects with progressive dysarthria were identified from the Euphonia dataset, a corpus of over 1 million speech samples from over 1000 individuals with impaired speech [16]. The Euphonia dataset was collected over several years and many of the subjects recorded over multiple months, allowing us to find cases with declining speech. The four subjects who were selected had (1) at least a 10% drop in ASR performance on the U-SI model over time, and (2) an increase in speech severity by at least two points between their first and last recording sessions. Speech recordings were binned into successive 30 day intervals so that, for example, speech recorded between the first and 30th day were coded as bin 1, and data recorded between
the 31st and 60th day from first recording were coded as bin 2. Speech severity ratings were first assigned to each 30-day bin. We then re-grouped these into fewer, purely severity based bins. E.g., for a speaker with a mild severity rating across two consecutive 30-day bins, all recordings were labeled as “mild” and collapsed into one bin. We obtained 3-4 severity-based bins per speaker (Table 1).

**Perceptual speech severity ratings.** Speech severity rating was completed by two licensed speech-language pathologists (SLP), who listened to at least 10 utterances from each original 30-day bin and rated overall speech severity on a Likert scale (typical, mild, moderate, severe, profound, and anarthric) [17]. The raters used professional-grade headphones and were allowed to adjust the gain as needed. Interrater reliability was assessed by computing a two-way, single measure model intraclass correlation coefficient which resulted in an ICC of 0.88 [18]. For the reliability analysis, the two SLPs rated speech severity for the same 50 recordings on a different dataset, part of the parent project.

**Selecting Utterances for experimentation.** The Euphonia dataset consists of recordings from different domains¹ which vary in average utterance length. To control confounding effects of utterance length we include only short phrases of 3-5 words in length. Such short phrases were chosen because those are most prevalent in the Euphonia dataset and we wanted to maximize the number of utterances per speaker (see Table 1 for a summary). Because the goal of this analysis was to compare model performance across different levels of speech degradation, we held the number of training data per speaker constant across the severity bins in order to not confound the model comparisons (see [15] on how training set size influences model personalization on impaired speech). We chose the training set sizes of each speaker to be as large as possible while leaving enough utterances per bin to be used as test set. These training set sizes can be thought of as a “budget” (i.e., the maximum number of utterances we assume a speaker to record). Table 2 shows the training set size per speaker. Training sets of the identified size were then randomly sampled per speaker from the recordings from each severity bin. From the remaining utterances we created test sets for each speaker per severity bin, ensuring no phrase overlap with their training sets. The same resulting test sets per speaker and per severity bin were used across all experiments ensuring comparability (see Table 1).

**Evaluation.** We calculated word error rate (WER) per severity bin and applied bootstrap sampling (1000 repetitions with replacement) to obtain estimates of the mean WER as well as 95% confidence intervals approximated by +/- 2 standard deviations.² For comparing personalized models, 95% confidence intervals (CIs) for the difference in WER within speaker were generated using bootstrap sampling as well, where CIs not overlapping 0 show significant difference between two strategies.

**ASR Models** We used end-to-end ASR models based on the well-studied RNN-T architecture [19], with an encoder network consisting of 8 layers and the predictor network of 2 layers of uni-directional LSTM cells. Inputs were 80-dimensional log-mel filterbank energies. Outputs were probability distributions over a 4k word piece model vocabulary.

The Unadapted Speaker Independent (U-SI) model was trained as described in [20], using ≈ 162k hours of typical speech (from Google’s internal production dataset). For the Adapted Speaker Independent (A-SI) model, we further fine-tuned the U-SI model on a large subset of the whole Euphonia dataset with the goal to provide a model that should work better out-of-the-box for impaired speech. For this, the Euphonia dataset was split into a training and a test set across

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¹E.g., home automation, caregiver requests, and conversational phrases.

²Analysis showed that the WER across samples was normally distributed.

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| Subject 1 | Subject 2 | Subject 3 | Subject 4 |
|-----------|-----------|-----------|-----------|
| # test utterances | # test utterances | # test utterances | # test utterances |
| severity | severity | severity | severity |
| days from baseline | days from baseline | days from baseline | days from baseline |
| MILD | MILD | MILD | MILD |
| 0 - 55 | 0 - 14 | 0 - 29 | 0 - 50 |
| MODERATE | MODERATE | MODERATE | MODERATE |
| 83 - 89 | 17 - 56 | 191 - 292 | 55 - 79 |
| SEVERE | SEVERE | SEVERE | SEVERE |
| 191 - 216 | 314 - 314 | 214 - 220 | 214 - 220 |
| PROFOUND | PROFOUND | PROFOUND | PROFOUND |
| 324 - 421 | 340 - 340 | 314 - 314 | 314 - 314 |

**Table 1.** Severity bins per speaker and resulting test set sizes. Days from baseline shows how many days have passed since speaker started recording.

**Table 2.** Number of training utterances per subject.
3. RESULTS

Impact of Degenerating Speech on ASR performance. We first compared the performance of the U-SI, the A-SI and the A-SD model personalized on the training data of the first severity bin per speaker to analyze the impact of degenerating speech on recognition performance. Figure 1 displays a progression charts. As expected, the U-SI models consistently performed the worst for all speakers and severity levels while the A-SD models performed best and the A-SI models were somewhere in between. An increase in severity consistently led to an increase in WER, especially in the higher severity levels. For Subject 2, recognition performance of the A-SD model was almost as poor as the U-SI model; in this case, even the A-SI performed slightly better. For Subject 3, the A-SI was not much worse than the A-SD model.

Mitigation Strategies. Based on our findings that the performance of personalized models degraded when trained on speech recorded during the early stage of speech impairment, we explored the effectiveness of two mitigation strategies for optimizing recognition during the most severe stages of speech decline when fewer training samples are typically available. In these experiments, the overall maximum number of training utterances was held constant (Table 2). We tested the performance of the A-SD models on the last severity bin, when WERs are highest. We compared the following 4 variants of the A-SD model:

- Baseline - 100% of data from bin 1 (as in Figure 1).
- Mitigation Strategy 1 (“start-over”) - Assuming we have used 50% of our recording budget on bin 1, we now use another 50% of recordings from the last severity bin. In the start-over scenario, we use only this 2nd 50% of recordings for adaptation.
- Mitigation Strategy 2 (“Continued Training”) - data allocation like in the start-over scenario but here we sim-
ultate training continuation in that we use both the bin 1 and bin 4 recordings for adaptation.

- Upper Bound - 100% of the recordings from bin 4 – this is an idealized and unpractical scenario only used to show the best possible performance if all training data is from the most recent severity level.

Figure 2 shows results for Subject 1 and Subject 2. The baseline model performed the worst of the four scenarios, while training on as much data as possible from the last severity phase resulted in the best recognition. While not surprising, these findings clearly show the negative impact of “outdated” data and how much, in contrast, a model can be improved by using the most recent data of the same size. Comparing the mitigation strategies (start-over and continued training), they both significantly improve WER over the baseline approach for both subjects. Continued training provided a significant improvement over the start-over strategy for Subject 2 but not for Subject 1. The upper bound scenario was significantly better than the mitigation strategies for both subjects, which emphasizes that doubling the number of recordings in later stages may be beneficial (if larger amounts of recordings are possible). Table 3 shows the 95% CIs for these comparisons.

### 4. DISCUSSION

This study investigated the impact of degrading speech on ASR accuracy in individuals with progressive dysarthria. Speech samples were recorded over time and selected to represent a substantial within-subject decline in speech. Recognition accuracy of the three ASR models decreased as speech degraded, particularly during the more severe stages of speech decline. To the best of our knowledge, this is the first time that the impact of speech degeneration on personalized models has been studied systematically.

Our experiments suggest that personalized models become less effective over the course of progression unless updated with more current recordings. Both the start-over scenario discarding “outdated” recordings, as well as continued training adding more recent data, significantly improved recognition when compared to recording all utterances upfront. Our experiments also suggest, that in absence of more recent data, keeping data from previous severity stages does not seem to incur any harm, but can improve performance.

Overall, our findings emphasize the importance of continued recording and model retraining when providing personalized models for individuals with progressive speech impairments. Amassing speech recordings during the early stage of the disease may be unnecessary if it is solely to improve future recognition when speech becomes more severe. Our finding that A-SI models can perform similar or even better than un-updated personalized models suggests that A-SI models may be a worthwhile option if re-recording is not possible.

These experiments were performed on a relatively small cohort of speakers. In the future, we plan to extend to more speakers and include other etiologies that lead to degenerating speech. We are currently recording a more controlled, longitudinal dataset with additional participants.

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