AUTOMATIC SEVERITY ASSESSMENT OF DYSARThRIC SPEECH BY USING SELF-SUPERVISED MODEL WITH MULTI-TASK LEARNING

Eun Jung Yeo\textsuperscript{1*}, Kwanghee Choi\textsuperscript{2*}, Sunhee Kim\textsuperscript{3}, Minhwa Chung\textsuperscript{1}

Department of Linguistics, Seoul National University, Republic of Korea\textsuperscript{1}
Department of Computer Science and Engineering, Sogang University, Republic of Korea\textsuperscript{2}
Department of French Language Education, Seoul National University, Republic of Korea\textsuperscript{3}

ABSTRACT

Automatic assessment of dysarthric speech is essential for sustained treatments and rehabilitation. However, obtaining atypical speech is challenging, often leading to data scarcity issues. To tackle the problem, we propose a novel automatic severity assessment method for dysarthric speech, using the self-supervised model in conjunction with multi-task learning. Wav2vec 2.0 XLS-R is jointly trained for two different tasks: severity level classification and an auxiliary automatic speech recognition (ASR). For the baseline experiments, we employ hand-crafted features such as eGeMaps and linguistic features, and SVM, MLP, and XGBoost classifiers. Explored on the Korean dysarthric speech QoLT database, our model outperforms the traditional baseline methods, with a relative percentage increase of 4.79% for classification accuracy. In addition, the proposed model surpasses the model trained without ASR head, achieving 10.09% relative percentage improvements. Furthermore, we present how multi-task learning affects the severity classification performance by analyzing the latent representations and regularization effect.

Index Terms— dysarthric speech, automatic assessment, self-supervised learning, multi-task learning

1. INTRODUCTION

Dysarthria is a group of motor speech disorders resulting from neuromuscular control disturbances, affecting diverse speech dimensions such as respiration, phonation, resonance, articulation, and prosody \cite{1}. Accordingly, people with dysarthria often suffer from degraded speech intelligibility, repeated communication failures, and, sequentially, poor quality of life. Hence, accurate and reliable speech assessment is essential for diagnoses and treatments, as it helps track the condition of patients and the effectiveness of treatments.

The most common way of assessing severity levels of dysarthria is by conducting standardized tests such as Frenchay Dysarthria Assessment (FDA) \cite{2}. However, these tests heavily rely on human perceptual evaluations, which can be subjective and laborious. Therefore, automatic assessments that are highly consistent with the experts will have great potential for assisting clinicians in diagnosis and therapy.

Research on automatic assessment of dysarthria can be grouped into two approaches. The first is to investigate a novel feature set. For instance, paralinguistic features such as eGeMAPS were explored on their usability for atypical speech analysis \cite{3}. Common symptoms of dysarthric speech provided insights into new feature sets - glottal \cite{4}, resonance \cite{5}, pronunciation \cite{6,7}, and prosody features \cite{8,9}. Further, representations extracted from deep neural networks were also examined, such as spectro-temporal subspace \cite{10}, i-vectors \cite{11}, and deepspeech posteriors \cite{12}. While this approach can provide intuitive descriptions of the acoustic cues used in assessments, it has the drawback of losing the information that may be valuable to the task.

The second approach is to explore the network architectures which take raw waveforms as input. Networks include but are not limited to distance-based neural networks \cite{13}, LSTM-based models \cite{14,15} and CNN-RNN hybrid models \cite{16,17}. As neural networks are often data-hungry, many researchers suffer from the data scarcity of atypical speech. Consequently, research has often been limited to dysarthria detection, which is a binary classification task. However, multi-class classification should also be considered for more detailed diagnoses. Recently, self-supervised representation learning has arisen to alleviate such problems, presenting successes in various downstream tasks with a small amount of data \cite{18,19}. Promising results were also reported for different tasks for atypical speech, including automatic speech recognition (ASR) \cite{20,21} and assessments \cite{22,23,24}. However, limited explorations were performed on the severity assessment of dysarthric speech.

This paper proposes a novel automatic severity assessment method for dysarthric speech using a self-supervised learning model fine-tuned with multi-task learning (MTL). The model handles 1) a five-way multi-class classification of dysarthria severity levels as the main task and 2) automatic speech recognition as the auxiliary task. We expect MTL to have two advantages for the automatic severity classification.
of dysarthria. First, the model is enforced to learn both acoustic and text features for severity classification. We hypothesize using these two complementary information can boost classification results. Second, the auxiliary ASR task can act as a regularizer, as the model is trained to focus on two different tasks. This can prevent overfitting to small data and yield better classification performances.

The rest of the paper is organized as follows: Section 2 introduces the proposed method, which consists of a self-supervised pre-trained model and fine-tuning with MTL. Section 3 describes the overall experimental settings and classification results. Then, Section 4 conducts further examinations, explaining how MTL can be so powerful. Finally, Section 5 is followed with a conclusion.

2. METHOD

This section demonstrates our automatic severity assessment method for dysarthric speech. The overview of the proposed method can be found at Figure 1. First, we briefly introduce the self-supervised pre-trained wav2vec-based models. Then, we describe the architectural modifications on the pre-trained model for multi-task learning. The model is fine-tuned on two tasks simultaneously: severity classification as the main task and ASR as the auxiliary task. We release the source codes of all the experiments for ease of reproduction.

2.1. Self-supervised pre-trained model

The key idea of self-supervised learning (SSL) models is to employ abundant unlabeled data to train a general speech model, namely, a self-supervised pre-trained model. Leveraged by the learned representations, the models have demonstrated promising results by fine-tuning with the limited size of datasets [18]. We expect the dysarthric speech domain, which often suffers from data scarcity, can also take advantage of this approach.

2.2. Fine-tuning by multi-task learning

We are motivated by the fact that speech intelligibility degrades with worse severity. Therefore, making decisions based on both acoustic and text features may boost classification results. To embody this domain knowledge into the severity classifier, we simultaneously trained the phoneme classifier as an auxiliary task. Moreover, multi-task learning is considered a regularization method that helps avoid overfitting. Considering the small size of dysarthric speech data, MTL can help further improvements in classification accuracy. In this paper, the most simple variant of MTL is employed for the two classifiers: hard parameter sharing with a linear combination of losses. The two classifiers share the self-supervised pre-trained model, with separate linear heads for each task.

Firstly, the raw audio signal $x \in [-1, 1]^L$ with length $L$ is fed into the model to yield $T$ latent speech representations $H = [h_1, h_2, ..., h_T] \in \mathbb{R}^{T \times F}$ of feature dimension $F$.

For the classification head, we average the latent representations and pass through the fully connected layer to yield logits for five-way severity classification, following [23]:

$$ h = \mathbb{E}[h_t] = \frac{1}{T} \sum_{t=1}^{T} h_t, $$

$$ p_{CE}(y|x) = \text{softmax}(W_{CE}h + b_{CE}), $$

where $h$ is the averaged representation, $W_{CE} \in \mathbb{R}^{5 \times F}$ and $b_{CE} \in \mathbb{R}^{5 \times 1}$ is the learnable weights and biases of the fully connected layer, and $F$ is the size of the feature dimension. We apply the cross-entropy loss $L_{CE}$ on the classification predictions $p_{CE}$.

For the ASR head, following [18] [19], we pass each latent representation $h_t$ at timestep $t$ through the common fully connected layer:

$$ p_{CTC}^t = \text{softmax}(W_{CTC}h_t + b_{CTC}), $$

where $p_{CTC}^t$ is the ASR prediction at timestep $t$, $W_{CTC} \in \mathbb{R}^{V \times F}$ and $b_{CTC} \in \mathbb{R}^{V \times 1}$ is the learnable weights and biases of the fully connected layer, and $V$ is the size of the vocabulary. We apply the Connectionist Temporal Classification (CTC) loss $L_{CTC}$ on stepwise ASR predictions $p_{CTC}^t$.

The final loss $L$ is designed as the linear combination of two losses:

$$ L = L_{CE} + \alpha L_{CTC}, $$

where $\alpha \in \mathbb{R}$ is the hyperparameter that balances the influence between two tasks. As $L_{CTC}$ tends to be few magnitudes larger than $L_{CE}$, we use $\alpha = 0.1$ in all of our experiments.

Also, the convergence speed hugely differs between $L_{CTC}$ and $L_{CE}$: $L_{CE}$ is much quicker, hence overfits before $L_{CTC}$ converges. To mitigate the problem, we only use $L_{CTC}$ in the initial $e$ epochs of training. We tested $e \in \{0, 10, 20\}$ out of 100 epochs of training for our experiments, and demonstrate the effectiveness of nonzero $e$ in Section 5.2.
3. EXPERIMENTS

3.1. Dataset

Quality of Life Technology (QoLT) dataset [25] is a Korean dysarthric speech corpus. The corpus contains utterances from 10 healthy speakers (5 males, 5 females) and 70 dysarthric speakers (45 males, 25 females), where five speech pathologists conducted intelligibility assessments on a 5-point Likert scale: healthy (0), mild (1), mild-to-moderate (2), moderate-to-severe (3), and severe (4). QoLT dataset contains isolated words and restricted sentences, but only sentences are used for this study, similar to [7, 9]. Accordingly, a total of 800 utterances are used, consisting of five sentences recorded twice per speaker.

We split train, validation, and test set speaker-independently in the ratio of 6:2:2 so that each set does not share the same speaker. The split is also stratified by gender. Table 1 presents the number of speakers for each set.

Table 1: Data split of QoLT dataset.

| Split  | healthy | mild | mild-mod | mod-severe | severe |
|-------|---------|------|----------|------------|--------|
| Train | M | F | M | F | M | F | M | F | M | F |
| 3 | 3 | 8 | 10 | 4 | 4 | 2 | 3 | 1 |
| Valid | 1 | 1 | 3 | 4 | 2 | 2 | 1 | 1 | 0 |
| Test  | 1 | 1 | 3 | 4 | 2 | 2 | 1 | 1 | 1 |

3.2. Experimental details

Following the findings from [20], we choose XLS-R [19] with 300M parameters, which is the self-supervised model trained with cross-lingual data, as the pre-trained model. We optimize the batch size of 4 using the Adam optimizer for 100 epochs. Similar to [19], we use the Adam parameters with learning rate $\gamma = 2 \times 10^{-5}$, $\beta_1 = 0.9$, $\beta_2 = 0.98$, and $\epsilon = 10^{-8}$. Using the validation set, we keep the best model with the final loss $C$. We report the best classification accuracy of three $e$s in table 2, where the best $e$ found was $e = 20$.

3.3. Baselines

For traditional features, we use (1) paralinguistic features, (2) linguistic features, and (3) their combination. As for paralinguistic features, we extract eGeMAPS feature set with the openSMILE toolkit [26]. Consisting of 25 low-level descriptors (LLDs) with 88 features, eGeMaps is a basic standard acoustic parameter set designed to capture various aspects of speech, including frequency-, energy-, spectral-, and temporal-related features. We also extract linguistic features used from the previous studies [7, 27]. The feature list was proposed to capture the common symptoms of dysarthria at different speech dimensions, such as voice quality, pronunciation (phoneme correctness, vowel distortion), and prosody (speech rate, pitch, loudness, rhythm). For the combined feature set, we simply concatenate the two feature lists.

Regarding classification, we apply three classifiers that showed successful results for dysarthria severity classification [9, 7, 27]: support vector machine (SVM), multi-layer perceptron (MLP), and XGBoost. The hyperparameters of the classifiers are optimized using grid search on the validation set. We optimize SVM with a radial basis kernel function in terms of $C$ and $\gamma$, by grid-searching both parameters between $10^{-4}$ and $10^4$. As for MLP, the best number of hidden layers, activation function, optimizer, and learning rate are searched. The number of hidden layers is checked between 1 and 10, activation function among tanh, relu, logistic, identity function, optimizer between Adam and SGD, and learning rate between $10^{-4}$ and $10^{-1}$. For XGBoost, we tested maximum depth between 3 and 5. To validate the effectiveness of multitask learning, we also conduct a single-training (STL) experiment, where the self-supervised model is fine-tuned without an auxiliary ASR task. All the hyperparameter settings are the same as our proposed method, but different in setting $\alpha$ as 0, to use only the classification loss $L_{ce}$ for training.

3.4. Results

Table 2 presents the performance of traditional baselines with fine-tuned SSL models, by using classification accuracy, precision (macro), recall (macro), and F1-score (macro). The best performance for each metric is indicated in bold.

Table 2: Classification accuracy with the baseline experiments.

| Input | Classifier | Accuracy     | Precision | Recall | F1-score |
|-------|------------|--------------|-----------|--------|----------|
| eGeMAPS | SVM        | 51.11        | 51.24     | 55.20  | 52.58    |
|        | MLP        | 42.22        | 40.09     | 46.80  | 42.12    |
|        | XGBoost    | 52.78        | 53.33     | 55.07  | 53.53    |
| Linguistic features | SVM | 49.44 | 53.44 | 57.20 | 54.36 |
|        | MLP        | 41.67        | 46.26     | 52.40  | 48.75    |
|        | XGBoost    | 54.44        | 54.24     | 63.53  | 56.66    |
| eGeMaps + Ling. | SVM | 48.33 | 51.77 | 55.13 | 53.26 |
|        | MLP        | 40.56        | 43.26     | 47.13  | 44.62    |
|        | XGBoost    | 57.78        | 58.18     | 64.67  | 60.07    |
| Raw audio | STL | 55.00        | 59.77     | 57.47  | 58.09    |
|        | MTL        | 60.55        | 62.93     | 64.33  | 62.37    |

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the experiment using the eGeMaps+linguistic feature set for XGBoost classifier, which shows 57.78% classification accuracy and 60.07% F1-score.

Last but not least, we analyze the performance of our proposed method in contrast to other baseline experiments. Our proposed method (MTL) achieves the highest accuracy, precision, and F1-score, with 60.55%, 62.93%, 62.37%, respectively. As for recall, XGBoost presents the best performance, while our proposed model obtains a comparative result.

4. ANALYSIS

4.1. Analysis on latent representations

The latent representations of the training set samples are analyzed to observe how fine-tuning shapes the latent representation space. For the analysis, we use the fully-converged model instead of the best-kept model, to demonstrate the representation space learned by the loss. Averaged representations $\hat{h}$ are visualized by using UMAP [28].

As plotted in Figure 2, representations from the STL model cannot be distinguished by utterances. In contrast, the representations are clustered in terms of both utterances and dysarthria severity levels for the MTL model. The analysis indicates that the MTL model also encodes reference text information. This result confirms our hypothesis, that considering both acoustic and text information for classification help boost performance. Note that unlike other severity levels, different utterances from mod-to-severe (3) and severe (4) dysarthric speakers are strongly clustered. We assume this may be due to significantly distorted speech, which makes it difficult for the ASR head to separate their representations.

4.2. Analysis on the regularization effect

Figure 3 presents the effect of MTL over STL (left) and the efficacy of postponing the $L_{CE}$ optimization for $e$ epochs (both). First, with joint optimization of CTC loss $L_{CTC}$ and CE loss $L_{CE}$, $L_{CE}$ overfits much slower than in STL, implying MTL’s regularization effect. Second, we observe more stable optimization and better performances on both classification and ASR tasks by setting $e$ to nonzero. This validates the effectiveness of aligning the convergence speed of the two losses. We suspect that premature training of $L_{CE}$ leads to choosing the model that is under-trained with the ASR task, which fails to inject enough text knowledge, resulting in worse classification performance.

5. CONCLUSION

This paper proposes a novel automatic dysarthria severity assessment method: a self-supervised model fine-tuned with multi-task learning. The XLS-R model, a cross-lingual self-supervised model, is fine-tuned to jointly learn the five-way severity classification task and the ASR task. Our proposed model achieves 62.37% F1-score, outperforming the traditional baseline experiments, which employ various handcrafted features (eGeMAPS, linguistic features) and machine learning classifiers (SVM, MLP, XGBoost). Moreover, we validate the effectiveness of MTL by comparing the performance to the STL model. Further analyses regarding the latent representations and regularization effect provide explanations for why our model with MTL is effective. Future research includes extending the applications of the proposed method to different corpora, languages, and disorders.

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