DDKtor: Automatic Diadochokinetic Speech Analysis

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Abstract

Diadochokinetic speech tasks (DDK), in which participants repeatedly produce syllables, are commonly used as part of the assessment of speech motor impairments. These studies rely on manual analyses that are time-intensive, subjective, and provide only a coarse-grained picture of speech. This paper presents two deep neural network models that automatically segment consonants and vowels from unannotated, untranscribed speech. Both models work on the raw waveform and use convolutional layers for feature extraction. The first model is based on an LSTM classifier followed by fully connected layers, while the second model adds more convolutional layers followed by fully connected layers. These segmentations predicted by the models are used to obtain measures of speech rate and sound duration. Results on a young healthy individuals dataset show that our LSTM model outperforms the current state-of-the-art systems and performs comparably to trained human annotators. Moreover, the LSTM model also presents comparable results to trained human annotators when evaluated on unseen older individuals with Parkinson’s Disease dataset.

Index Terms: Diadochokinetic speech, DDK, Deep neural networks, Voice onset time, Vowel duration, Parkinson’s Disease

1. Introduction

Diadochokinetic (DDK) speech tasks are commonly used by clinicians and researchers as part of the assessment of speech motor impairments [1, 2]. In the alternating motion rate (AMR) version of this task, participants repeatedly produce particular syllables as quickly and accurately as possible (e.g., pa-pa-pa..., ta-ta-ta..., or ka-ka-ka...). In the sequential motion rate (SMR) task, a syllable sequence is repeatedly produced (e.g., pa-ta-ka-pa-ta-ka...). These tasks help clinicians evaluate the patient’s speech motor control and ability to make rapidly alternating speech movements. These tasks have been shown to be useful for impairment detection, differential diagnosis, and course monitoring and have, consequently, become a part of many speech/neurological assessments [3, 4].

For a measurement that has been proven to be important in patient care, the outcome measures in use are surprisingly basic, with clinicians evaluating the patient impressionistically and/or counting how many syllables the patients were able to produce in a certain amount of time and comparing that against established norms. While these measures are easy for clinicians to obtain, impressionistic evaluation is inherently subjective, and previous work has suggested that both of these measures have relatively low inter- and intra-rater reliability [4] (but see [5]). These measures also provide a highly impoverished picture of speech. The acoustics of DDK productions provide information about the temporal and spectral properties of syllables and individual speech sounds as well as more complex measures of speech rate (e.g., variance, irregularity). While such measures have been studied in research settings by manually annotating the speech [6], this approach is clearly impractical in a clinical setting.

Automated, objective measurement of more detailed properties of untranscribed, unannotated DDK speech could provide a means of addressing these issues without placing additional burdens on valuable clinician time. Previous studies focused on automatic annotation of a single property. Signal processing methods [7] and deep learning methods utilizing convolutional neural networks (CNNs) [8, 9] have been used to segment syllables, allowing for automatic calculation of speech rate. Another line of works has been focused on measuring voice onset time (VOT). Montañá et al. [10] proposed an expert system that is based on temporal and spectral features, and Arias-Vergara et al. [11] proposed to use a deep learning approach that utilized a bi-directional recurrent neural network on manually extracted time and spectral acoustic features. As far as we know, only Novotný et al. [12] suggested an automated segmentation of both VOT and vowels, by using a representation similar to [10] without deep learning.

In this paper, we suggest two novel deep learning models for automatic segmentation of unannotated diadochokinetic speech. Our models are unique as they allow an accurate segmentation of both vowels and VOTs, with the flexibility of using variable-length processing window and by working directly on the raw waveform. These architectures eliminate the need of a restrictive representation and translate to a more accurate measurement of the speaking rate. Using DDK samples from both healthy individuals and individuals with Parkinson’s Disease (PD), we show that our model outperforms the current state-of-the-art and performs comparably to trained human annotators. The implementation of our models is available at: https://github.com/MLSpeech/DDKtor.
2. Model

In the DDK task, we are provided with an audio signal containing an alternating sequence of a positive-lag VOT (for each voiceless stop consonant) followed by the vowel (a). Our goal is to segment the audio signal according to three acoustic objects: VOT, vowel, and other/silence. Hence, the input to our models is the raw audio and the output is a sequence of objects and their timings.

For raw audio of duration T, we denote the input sequence of samples by \( x = (x_1, \ldots, x_T) \), where \( x_t \in \mathbb{X} \) for all \( 1 \leq t \leq T \) and \( \mathbb{X} \subset \mathbb{R} \). We represent the output as a sequence of 1 millisecond frames, \( \tilde{y} = (y_1, \ldots, y_K) \), where there are \( K \) frames, and \( y_k \in \mathbb{Y} = \{ \text{VOT, vowel, other} \} \) for \( 1 \leq k \leq K \). Note that the signal duration \( T \) and the number of output frames \( K \) can vary from one signal to another, and thus these quantities are not fixed.

Our models are composed of two functions. The features extraction function \( g: \mathbb{X} \rightarrow \mathbb{Z}^K \) is a function from the domain of \( \mathbb{X} \) to the domain of an abstract latent representation \( \mathbb{Z} \subset \mathbb{R}^N \). Namely, the features extraction function generates a sequence of embedding vectors \( \tilde{z} = (z_1, \ldots, z_K) \). Each vector \( z_k \in \mathbb{Z} \) represents the acoustic content of the \( k \)-th frame. The feature vector sequence is then processed by a classification function that outputs a sequence of \( K \) predictions.

The classifier function \( f: \mathbb{Z}^K \rightarrow \mathbb{Y}^K \) from the domain of features vectors to the domain of target objects.

The functions \( g \) and \( f \) are implemented using deep learning functions by two models. The first model is depicted in the top panel of Figure 1. This model, a convolutional neural network (CNN) is used as a features extraction function, \( g \). It has five 1D convolutional layers with batch normalization, a leaky-ReLU activation function, and dropout between each layer. The features extractor output is then forwarded to the classifier \( f \), composed of a two-layer bi-directional long short-term memory (LSTM) and two fully-connected (FC) layers. This model will be denoted as DDKtor-LSTM.

The second model is depicted in the bottom panel of Figure 1. In this model, a convolutional neural network (CNN) is used as a features extraction function, \( g \). It has five 1D convolutional layers with batch normalization, a leaky-ReLU activation function, and dropout between each layer. The output of the CNN is forwarded to two FC layers. This model will be denoted as DDKtor-CNN.

The parameters of both models are trained to minimize the cross-entropy loss function. For both models, a post-processing procedure is used to convert the frame-based to segment-based predictions. First, we group together frames with the same object type. Second, we mark short VOTs (less than 5 milliseconds), and short vowels (less than 20 milliseconds) as silence. Finally, we convert a short silence (less than 20 milliseconds) between two VOT segments to a single VOT segment.

3. Datasets

In our experiments, we used two datasets of DDK productions in English. Both datasets were annotated for VOTs and vowel durations by two independent annotators. The first is called the Younger NT Adults dataset, and it includes speech from the AMR and SMR subtasks for 92 neurotypical adult participants (mean age in their early twenties), collected in a laboratory environment as pre-test data in speech motor learning experiments [14, 15]. The speech signals were sampled at 44.1 kHz with 16-bit resolution. Participants were randomly split into training (\( N = 55 \), AMR \( \sim \) 9 minutes, SMR \( \sim \) 3 minutes), validation (\( N = 18 \), AMR \( \sim \) 3 minutes, SMR \( \sim \) 1 minutes), and test (\( N = 19 \), AMR \( \sim \) 4 minutes, SMR \( \sim \) 2 minutes).

To test the ability of the algorithm to generalize to laboratory speech from individuals with motor speech impairments, we used a second dataset called the Older PD Adults. This dataset contains the AMR and SMR subtasks from \( N = 5 \) older adults with Parkinson’s Disease (PD), aged 59-77 years old. These were selected from the Ontario Neurodegenerative Disease Research Initiative (ONDRI), a longitudinal, multisite, observational cohort study, using a transdisciplinary approach to characterizing deep endophenotypes in neurodegenerative disorders and their relationship to cerebrovascular disease [16, 17]. The speech signals were sampled at 44.1 kHz with 16-bit resolution. Manual analysis conducted prior to this study, focusing solely on the five selected individuals, had extracted for each speaker \( \sim \) 5 seconds from the AMR subtask production for each VOT and \( \sim \) 5 seconds from the SMR subtask (syllables were left intact). Note that this dataset was used only to evaluated our model and not for training.

4. Experiments

4.1. Details

Both DDKtor-LSTM and DDKtor-CNN were trained with a batch size of 32. We optimized parameters with the Adam optimizer [18] and a learning rate of 0.0001. The audio files were resampled at 16 kHz. Long audio files were divided into one-second segments. We utilized data augmentations to increase the robustness of the algorithm. We used the package WaveAugment [19] to augment the data using: (i) clean speech; (ii) noisy speech\(^1\) with signal-to-noise ratio of 5, 10, 15 dB; and (iii) band-reject filtered speech (removing randomly selected spectral components). We also randomly shifted the starting frame of each one-second input for generating different inputs lengths.

We compared our models against the state-of-the-art model Arias-Vergara et al. [11]. We trained it on Younger NT Adults dataset, without using data augmentation, as it dramatically reduced performance. We also compared our model against Räsänen et al. [7], which presents an algorithm for segmentation of syllables-like objects. Hence we compare it only for the Diodochokinetik speech rate task, using the best parameters they reported in their study (\( f = 8 \) Hz, \( Q = 0.8 \), and \( \delta = 0.01 \)). Implementations of [8, 9, 10, 12] were not available.

4.2. Evaluation and Results

We evaluate model performance against the gold standard: measures derived from manual annotations (we compare against one annotator; see the GitHub repository for results against the second annotator). As a benchmark of the performance, we also provide measures of inter-annotator agreement denoted as Annotators. Below, we report results on the two unseen test sets we consider.

\(^1\)We added car-noise from [20] package, which we found most similar to the air condition noise often evident in the datasets, although other noises work similarly.
4.2.1. Diadochokinetic speech rate

DDK rate is defined as the number of syllables produced divided by total articulation time. That is, the time elapsed between the VOT onset of the first produced syllable and the vowel offset of the final produced syllable. Four different rates were calculated for each participant (one for each syllable of the AMR task; one for the SMR task).

We analyzed the decisions of DDKtor-LSTM and DDKtor-CNN and found that both models sometimes merge two adjacent syllables (treated flap t’s as a part of the vowel). To automatically account for this issue, we incremented the syllable count every time the duration of a predicted vowel was more than twice the participant’s average vowel duration. The model of [11] sometimes skips VOTs. We made a similar adjustment by incrementing syllable count whenever the time elapsed between two VOTs was more than twice the participant’s average inter-VOT duration. Additionally, note that because [11] estimates only VOT, it cannot calculate total articulation time (which requires a value for total syllable length, including VOT and vowel duration). To ensure a fair comparison, for all models we estimated total articulation time using a manually-annotated window encompassing the full set of syllables.

Table 1 presents the correlations and mean absolute errors between the model and the annotator. DDK rates predicted by our models were highly correlated with those of the annotator. Of the four models, the DDKtor-LSTM model performed the best, achieving correlations of 0.94 and 0.99. It successfully predicts DDK rates from completely unannotated DDK samples in a way that generalizes across datasets and populations.

4.2.2. Segment duration and boundaries

Recall that we group frames with the same predicted object type to a single segment. The model performance are measured at the segment level, and we analyze how the accuracy of the predicted boundaries and the durations of both VOT and vowel segments.

Table 2 presents F1-scores for VOT and vowel segments detection for each models by dataset (cf. [21]). It seems that the F1-scores for all models are high, while DDKtor-LSTM shows the high-
Table 2: F1-scores for VOT and vowel segments prediction.

|                      | Younger NT Adults | Older PD Adults |
|----------------------|-------------------|-----------------|
|                      | VOT F1            | Vowel F1        |
| DDKtor-LSTM          | 0.978             | 0.985           |
| DDKtor-CNN           | 0.959             | 0.957           |
| Arias-Vergara et al. [11] | 0.945          | 0.950           |

Table 3: Correlations between model and annotator durations by dataset (mean absolute errors in parentheses). Bolded values represent the best-performing models within each column (VOT or Vowel in each dataset). All correlations are significant with p < 1e-33.

|                      | Younger NT Adults | Older PD Adults |
|----------------------|-------------------|-----------------|
|                      | VOTs              | Vowels          |
| DDKtor-LSTM          | 0.97 (0.004)      | 0.97 (0.007)    |
| DDKtor-CNN           | 0.85 (0.004)      | 0.84 (0.009)    |
| Arias-Vergara et al. [11] | 0.80 (0.006)  | -               |
| Annotators           | 0.93 (0.003)      | 0.94 (0.004)    |

Table 4: Mean absolute deviation in boundary offsets (milliseconds) by dataset.

|                      | VOT Onset | VOT Offset/ Vowel Onset | Vowel Offset |
|----------------------|-----------|-------------------------|--------------|
| Younger NT Adults    | DDKtor-LSTM | 1.88                    | 2.96         | 6.34          |
| Older PD Adults      | DDKtor-LSTM | 3.08                    | 6.24         | 3.43          |

5. Conclusions

Automated analysis of fine-grained acoustic properties of disadochokinetic speech could provide new insights into speech motor disorders without increasing burdens on clinicians and researchers. In this paper, we presented two new algorithms for segmenting VOTs and vowels from unannotated DDK samples and compared their performance against the current state-of-the-art deep learning model [11] and signal processing model [7]. We evaluated the models in their ability to (i) predict DDK rate and (ii) identify duration and boundary location of consonants and vowels. We found that, in general, DDKtor-LSTM achieved better performance than DDKtor-CNN, which suggests that recurrent neural network (RNN) cannot be entirely replaced by CNN for sequential tasks. Overall, DDKtor-LSTM achieved state-of-the-art performance on unannotated speech, performing almost as well as human annotators across two datasets.

These systems could allow for more nuanced, detailed, and objective measures of DDK samples. The temporal boundaries extracted here can inform many other acoustic analyses. These include: spectral analysis of VOTs and vowels (e.g., burst spectra, formant properties); and more detailed analysis of the temporal/metrical properties of production (e.g., variability in speech rate over a trial). As measurement is automatic, such analyses can be conducted over many trials and individuals, allowing for more detailed assessment of the distributional properties of measures.

There are several aspects of the model that can be improved in future work. As noted above, the model misses syllables, especially when the participant flaps /t/. We have also noted poor performance on a small number of individuals with high degrees of creaky phonation. More extensive training on these less frequent acoustic variants (flaps, creaky voice) may improve performance. In addition, this model was applied only to voiceless targets; future work can extend this approach to examine AMR and SMR subtasks using voiced variants. Finally, the model’s robustness to variation in recording conditions should be examined (e.g., by analysis of speech collected outside of acoustically controlled laboratory environments).

In conclusion, we have introduced a deep neural network model, DDKtor-LSTM, which reliably extracts clinically useful information from completely untranscribed and unannotated DDK samples. This algorithm can allow for more detailed automatic analyses of DDK samples, providing new insights into motor speech behavior.

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