Interspeech 2018
2-6 September 2018, Hyderabad

A Multitask Learning Approach to Assess the Dysarthria Severity in Patients with Parkinson's Disease

J. C. Vásquez-Correa[1,2], *T. Arias-Vergara*[1,2,3], *J. R. Orozco-Arroyave*[1,2], *and E. Nöth*[2]

[1]Faculty of Engineering, University of Antioquia UdeA, Calle 70 No. 52-21, Medellín, Colombia.
[2]Pattern Recognition Lab, Friedrich-Alexander-University Erlangen-Nüremberg, Germany.
[3]Ludwig-Maximilians-University, Munich, Germany

jcamilo.vasquez@udea.edu.co

Abstract

Parkinson's disease is a neurodegenerative disorder characterized by a variety of motor and non-motor symptoms. Particularly, several speech impairments appear in the initial stages of the disease, which affect aspects related to respiration and the movement of muscles and limbs in the vocal tract. Most of the studies in the literature aim to assess only one specific task from the patients, such as the classification of patients vs. healthy speakers, or the assessment of the neurological state of the patients. This study proposes a multitask learning approach based on convolutional neural networks to assess at the same time several speech deficits of the patients. A total of eleven speech aspects are considered, including difficulties of the patients to move articulators such as lips, palate, tongue, and larynx. According to the results, the proposed approach improves the generalization of the convolutional network, producing more representative feature maps to assess the different speech symptoms of the patients. The multitask learning scheme improves in of up to 4% the average accuracy relative to single networks trained to assess each individual speech aspect.

Index Terms: Parkinson's disease, Dysarthria assessment, Multitask learning, Articulation analysis

1. Introduction

Parkinson's disease (PD) is a neurological disorder characterized by the progressive loss of dopaminergic neurons in the midbrain, producing several motor and non-motor impairments [1]. Motor symptoms include bradykinesia, rigidity, resting tremor, micrographia, and different speech impairments, which are currently evaluated according to the third section of the movement disorder society-unified Parkinson's disease rating scale (MDS-UPDRS-III) [2]. Only one of the 33 items of the MDS-UPDRS-III scale is related to speech; however, the majority of PD patients develop several speech disorders [3]. Those disorders are considered as an early sign of further motor impairments [4]. The most common symptoms in the speech of PD patients include reduced loudness, monopitch, monoloudness, reduced stress, breathy, hoarse voice quality, and imprecise articulation. These impairments are grouped together and called *hypokinetic dysarthria* [3]. One of the first observed impairments was the imprecise production of stop consonants such as /p/, /t/, /k/, /b/, /d/, and /g/ [3]. A reduction of the articulatory precision in stop consonants was also observed in [5]. From the technical point of view, the speech impairments developed by PD patients have been described computing features related to four dimensions: phonation, articulation, prosody, and intelligibility [4, 6, 7]. Although the already known success of these classical feature extraction approaches, in the recent years deep learning methods have been successfully implemented to assess specific phenomena in speech, including the detection and monitoring of PD [8, 9]. For instance, in [8], the winners of the "2015 computational paralinguistic challenge (ComParE)" [10] evaluated the neurological state of PD patients according to the MDS-UPDRS-III score using Gaussian processes and deep neural networks (DNN). The authors automatically grouped the speech tasks per speaker and reported a Spearman's correlation (ρ) of 0.65. In [11] the authors proposed a deep learning model to assess the severity of dysarthria. The model considered an intermediate interpretable hidden layer to model four perceptual dimensions: nasality, vocal quality, articulatory precision, and prosody. The interpretable output of the DNN was highly correlated (ρ =0.82) with a subjective evaluation provided by speech and language pathologists. In [12] the authors modeled the voice quality spectrum in PD using a deep learning approach to compute phonological posteriors from the speech signal. Those posteriors were used to assess the dysarthria level of 50 PD patients and 50 healthy control (HC) speakers. The authors correlated (ρ=0.56) the predicted scores and the subjective evaluation performed by speech therapists. In [9] the authors modeled articulation impairments of PD patients with time-frequency representations and convolutional neural networks (CNNs) with the aim to assess the difficulties of the patients to start and stop the vibration of the vocal folds. The authors classified PD patients and HC speakers considering speech recordings in three languages: Spanish, German, and Czech, and reported accuracies from 70% to 89%, depending on the language. For Spanish, accuracies of 85.5% are obtained, using the same data from this study.

Most of the studies consider only one specific task to evaluate the speech of PD patients e.g., to classify PD patients vs. HC subjects [4, 9], to evaluate the neurological state of PD patients [8], or to assess the general speech impairments of the patients [11, 12]. The multitask learning approach offers the possibility to evaluate several deficits simultaneously. This study proposes a multitask learning strategy based on CNNs to assess the severity of different speech aspects that are impaired in PD patients, including respiration capability, larynx movement capacity, lips movement capacity, monotonicity, among others. The assessment of these aspects is performed according to a modified version of the Frenchay dysarthia assessment scale (m-FDA), which was introduced recently [6, 13]. We also consider standard tasks such as the classification of PD vs. HC subjects, the assessment of the neurological state of the patients according to the MDS-UPDRS-III score, and the assessment of the speech item of the MDS-UPDRS-III score. A total of eleven tasks are considered in this study with the multitask learning approach. We train the CNNs for the multitask learning based on

10.21437/Interspeech.2018-1988

the articulatory model presented in [9], which is used to model the difficulties of the patients to start/stop the vibration of the vocal folds based on the transition between voiced and unvoiced segments. The multitask learning strategy aims to improve the generalization of feature maps learned by the CNN. The results suggest that it is possible to assess specific speech symptoms of the patients following the introduced strategy. The results also indicate that to train CNNs with multiple tasks may provide more representative feature maps than specific CNNs trained to classify each task separately. The multitask learning approach also provide an improvement relative to the reported previously with the same data and the same features [9].

2. Methods

2.1. Transition modeling

A transition in speech occurs when the speaker starts or stops the vocal fold vibration. We detect the transition from unvoiced to voiced segments (onset) and from voiced to unvoiced (offset), which are segmented according to the presence of the fundamental frequency F_0 using Praat. Once the borders are detected, 80 ms of the signal are taken to the left and to the right of each border, forming "chunks" of signals with 160 ms length [14]. Each chunk is transformed into a time frequency representation using the short-time Fourier transform. The transformed signal is used as input to the deep learning architecture for the multitask learning scheme.

2.2. Multitask learning

We aim to evaluate the speech deficits of PD patients that appear due to dysarthria. The multitask learning architecture is based on a CNN where convolutional and pooling layers are shared across the tasks. Multitask learning improves generalization in the training process of a deep learning model [15]. When part of the CNN is shared across different tasks, the feature maps are more constrained, yielding better generalization. We consider the same approach than the proposed in [9], i.e., modeling the onset and offset transitions. This approach might be suboptimal for some of the tasks assessed in this study, specially those not related to articulation impairments; however, we believe that including all tasks in the learning process may help to improve the results for other tasks, which are related to the articulation deficits of the patients.

Figure 1 shows the CNN architecture used in this study. The CNN is formed with four convolutional and two pooling layers that are shared for all tasks. After the last pooling layer, an individual hidden fully connected layer is used per task, followed by the output layer to take the final decision using a sigmoid activation function. The loss function in a multitask strategy is a linear combination of the individual loss functions for each task, following Equation 1 when two tasks are considered. The term γ is a weight hyper-parameter, $L_1(\Theta)$ is the loss for the first task, and $L_2(\Theta)$ is the loss function for the second task. When $\gamma = 0$, the CNN only learns the first task, and when $\gamma = 1$, the CNN is trained to predict only the second task. The loss function can be generalized using Equation 2 when more than two tasks are considered, subject to the condition $\sum_i \gamma_i = 1$.

$$L(\Theta) = \gamma L_1(\Theta) + (1-\gamma)L_2(\Theta) \quad (1)$$

$$L(\Theta) = \sum_i \gamma_i L_i(\Theta) \quad (2)$$

The CNNs are trained using the stochastic gradient descent algorithm. The cross–entropy between the training labels y and the model predictions $\widehat{y}$ is used as loss function L_i. The root mean square propagation is considered to adapt the learning rate in each iteration [16]. Additionally, rectifier linear (ReLU) activation functions are used in the convolutional layers, dropout is included in the training stage to avoid over-fitting, and batch normalization is used to accelerate the training process.

2.3. Validation

The experiments are validated with the following strategy: 80% of the data are used for training, 10% of the data are used to optimize the hyper-parameters, i.e., development set, and the remaining 10% are used for test. The process is repeated 10 times with different partitions of the test set to guarantee that every participant is tested once. The hyper-parameter tuning is performed with a Bayesian optimization approach [17]. The tuning process is based on an optimization problem, where we find the hyper-parameters that maximize the performance of the model on the development set. The range of the hyper-parameters to be optimized is shown in Table 1. A batch-size of 128 samples and a total of 100 epochs are considered.

Table 1: *Range of the hyper-parameters used to train the CNNs.*

Hyper-parameter	Values
Filter size convolutional layers	$\{3, 5, 7\}$
Depth of convolutional layers	$\{4, 8, 16, 32, 64\}$
Hidden units in fully connected layers	$\{16, 32, 64, 128\}$
Learning rate	$\{0.0001, 0.0005, 0.001\}$
Probability of dropout	$\{0.1, 0.2 \cdots 0.9\}$
Weight factor for multitask γ_i	$\{0.1, 0.2 \cdots 0.9\}$

3. Data

3.1. m-FDA scale

In order to help language therapists and patients to assess the communication abilities of PD patients, we developed a modified version of the FDA [18] scale (m-FDA), which can be administered based on speech recordings. This scale evaluates several aspects of speech: respiration, lips movement, palate/velum movement, larynx, tongue, monotonicity, and intelligibility. The m-FDA scale contains 13 items and each of them ranges from 0 (completely healthy) to 4 (very impaired), thus the total score of the scale ranges from 0 to 52 [6, 12]. The scale is in the process of clinical validation. The labeling process of the m-FDA was performed by three phoniatricians, who agree on the evaluations of the first ten speakers (randomly chosen). Afterwards, the experts evaluated the remaining recordings independently. The inter-rater reliability among the phoniatricians was 0.75, which was computed calculating the average Spearman's correlation between all possible pairs of raters [13]. Table 2 summarizes the speech aspects and items included in the evaluation. For the multitask learning approach we aim to predict these individual aspects of the m-FDA score. Each aspect corresponds to a task in the multitask learning scheme.

3.2. Participants

We consider the PC-GITA database [19]. The data contain speech utterances from 50 PD and 50 HC Colombian native speakers balanced in age and gender. The participants pronounced several utterances including the rapid repetition of the

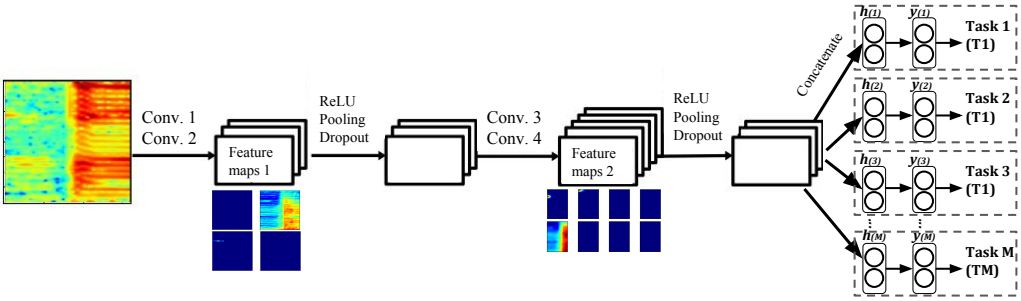

Figure 1: *Multitask learning architecture based on CNNs to assess the dysarthria impairments in PD patients*

Table 2: *List of aspects and items included in the m-FDA evaluations*

Aspect	m-FDA items
Respiration	1) Duration of respiration 2) Respiratory capacity.
Lips	3) Strength of closing the lips. 4) General capacity to control the lips.
Palate/Velum	5) Nasal escape. 6) Velar movement.
Laryngeal	7) Phonatory capacity in vowels. 8) Phonatory capacity in continuous speech. 9) Effort to produce speech.
Tongue	10) Velocity to move the tongue in /pa-ta-ka/. 11) Velocity to move the tongue in /ta/.
Intelligibility	12) General intelligibility.
Monotonicity	13) Monotonicity and intonation.

syllables /pa-ta-ka/, /pa-ka-ta/, /pe-ta-ka/, /pa/, /ta/, /ka/, isolated sentences, a read text, and a monologue.Additional information from the participants is shown in Table 3. In addition, the distribution of the total m-FDA and the MDS-UPDRS-III scales is shown in Figure 2 for the participants of this study.

Table 3: *Information of the participants from this study*

	PD patients		HC subjects	
	male	female	male	female
Number of subjects	25	25	25	25
Age ($\mu \pm \sigma$)	61.3±11.4	60.7±7.3	60.5±11.6	61.4±7.0
Range of age	33-81	49-75	31-86	49-76
Duration of the disease ($\mu \pm \sigma$)	8.7±5.8	12.6±11.6	-	-
MDS-UDRS-III ($\mu \pm \sigma$)	37.8±22.1	37.6±14.1	-	-
MDS-UDRS-III speech ($\mu \pm \sigma$)	1.4±0.9	1.3±0.7	-	-
Total m-FDA ($\mu \pm \sigma$)	29.8±8.6	28.2±9.0	7.6±9.2	5.1±7.3
m-FDA Respiration ($\mu \pm \sigma$)	5.3±8.5	4.8±2.0	1.1±1.5	0.5±1.0
m-FDA Lips ($\mu \pm \sigma$)	4.0±1.9	3.0±1.7	0.6±0.9	0.5±1.4
m-FDA Palate ($\mu \pm \sigma$)	5.0±1.8	5.0±1.8	1.5±1.9	1.2±1.8
m-FDA Larynx ($\mu \pm \sigma$)	7.0±2.8	6.0±2.7	1.5±2.3	0.8±1.5
m-FDA Montonicity ($\mu \pm \sigma$)	2.0±0.8	2.0±0.9	0.5±0.8	0.3±0.5
m-FDA Tongue ($\mu \pm \sigma$)	5.0±1.8	5.0±2.0	2.0±2.5	1.5±2.4
m-FDA Intelligibilty ($\mu \pm \sigma$)	2.0±1.0	1.0±0.7	0.4±0.5	0.3±0.7

4. Experiments and Results

The first experiment consists of training a multitask learning approach considering eleven tasks to evaluate specific speech impairments of the patients (see Table 4). We grouped the speakers into three or four classes per task according to the severity of the symptoms per task. The number of classes was determined to guarantee balanced groups in the tasks.

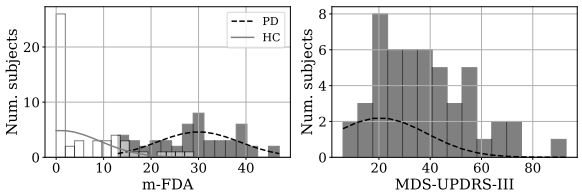

Figure 2: *m-FDA score for the PD patients and HC subjects (left), MDS-UPDRS-III scores for the PD patients (right)*

Table 4: *Description of the Tasks considered for the multitask learning approach*

Task	Description	N. classes
Task 1.	PD. vs. HC	2
Task 2.	Total MDS-UPDRS-III	4
Task 3.	speech item MDS-UPDRS-III	4
Task 4.	Total m-FDA	4
Task 5.	m-FDA Respiration aspect	4
Task 6.	m-FDA Lips movement aspect	4
Task 7.	m-FDA Palate movement aspect	4
Task 8.	m-FDA Larynx movement aspect	4
Task 9.	m-FDA monotonicity aspect	3
Task 10.	m-FDA Tongue aspect	4
Task 11.	m-FDA Intelligibility aspect	3

Multitask CNNs are trained with information of the onset and offset transitions, and the results are compared to those obtained training single CNNs per task. The results are shown in Table 5. Average results show an improvement in the accuracy when the multitask learning is considered (up to 4% for offset).

Higher results are obtained with the multitask learning for some of the individual tasks, specially in offset. Note the improvement for the PD vs. HC task (UAR from 79% to 89%), for the m-FDA tongue assessment (UAR from 40.7% to 53.8%), and for the m-FDA larynx evaluation (UAR from 34.9% to 42.6%). The tasks related to the articulation capabilities e.g., m-FDA lips, larynx, and tongue are those that provide the largest improvements in the multitask scheme, which is explained due to the proposed model is more related to assess the articulation capabilities of the patients. The results for some tasks, e.g., m-FDA monotonicity, respiration, and intelligibility could be improved considering a more specific model to assess such aspects, which may not be related to the ransition modeling.

The second experiment consists of modeling two tasks re-

Table 5: *Results obtained for a multitask learning approach to classify eleven tasks related to speech impairments of PD patients.* ***ACC:*** *Accuracy (%),* ***UAR****: Unweighted average recall (%). The bold UARs correpond to the best result obtained per task, for onset and offset*

Task	N. classes	Multitask onset		Single task onset		Multitask offset		Single task offset	
		ACC.	UAR	ACC.	UAR	ACC.	UAR	ACC.	UAR
PD vs HC	2	85.0±10.8	85.0	86.0±2.7	**86.0**	89.0±7.7	**89.0**	79.0±6.7	79.0
Total MDS-UPDRS-III	4	55.4±9.4	**55.2**	51.2±8.1	41.0	55.5±11.4	38.8	52.0±10.5	**41.5**
MDS-UPDRS-speech	4	57.8±11.8	**51.7**	50.4±10.6	38.3	56.8±14.4	**47.0**	54.2±9.1	33.6
Total m-FDA	4	45.2±6.7	43.3	46.8±7.8	**43.8**	44.3±8.4	40.3	43.0±3.8	**42.9**
m-FDA respiration	4	40.7±4.2	**44.7**	42.8±1.1	41.2	40.8±15.2	37.6	44.3±11.9	**42.4**
m-FDA lips	4	54.3±6.3	**51.4**	49.3±4.2	49.0	43.8±3.3	31.1	41.7±7.7	**33.3**
m-FDA palate	4	43.6±2.4	**37.6**	41.4±5.3	33.6	39.8±14.2	31.1	39.7±5.8	**34.5**
m-FDA larynx	4	46.2±8.5	43.2	44.5±5.7	**44.4**	43.4±6.6	**42.6**	35.9±10.6	34.9
m-FDA monotonicity	3	49.6±10.1	49.7	50.1±11.5	**59.6**	50.6±3.2	**50.3**	44.4±9.8	32.8
m-FDA tongue	4	43.9±4.2	**43.1**	48.8±9.9	42.6	54.3±6.9	**53.8**	39.5±4.3	40.7
m-FDA intelligibility	3	68.4±6.5	57.8	70.0±8.6	**67.5**	69.5±6.3	**68.2**	69.5±6.3	67.4
Average		**53.6**	**51.1**	**52.9**	**49.8**	**53.5**	**48.2**	**49.4**	**43.9**

lated to classification and regression: (1) the classification of PD vs. HC subjects, and (2) a regression task to predict the total m-FDA score. Figure 3 shows the result of the multitask learning when the value of the hyper-parameter γ in the loss function (see Equation 1) ranges from 0.1 to 0.9. Figure includes the accuracy for the classification task (black curve) and the Spearman's correlation ρ for the regression task (gray curve). Both metrics are computed on the development set to optimize the hyper-parameter γ. The results for both tasks follow a similar trend when γ ranges from 0.1 to 0.5. Then, the accuracy for the classification task improves while the correlation for the regression task start to decrease, which is expected because the global loss function gives more weight to the classification task when $\gamma > 0.5$. The results are compared to those obtained with the single learning (see Table 6). The results for the multitask learning are always higher than those obtained when single CNNs are trained for each task. There is also a smaller reduction in the results obtained for the development and test sets when we consider the multitask learning. This fact confirms the better generalization provided by the proposed scheme.

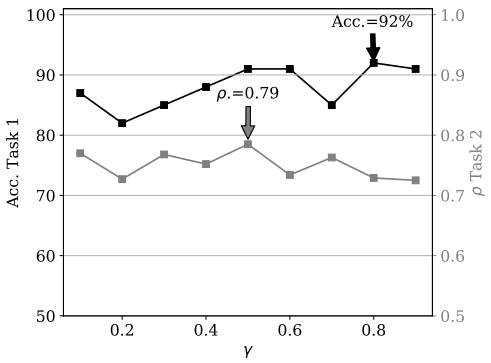

Figure 3: *Results on the development set when the loss function of the CNN include the classification of PD vs. HC subjects (Task 1) and the prediction of the total m-FDA score (Task 2), depending on the parameter of the loss function γ.*

5. Conclusions

A multitask learning scheme is proposed in this study to assess the severity of different speech impairments that appear in PD patients. A deep learning approach based on CNNs is considered for the multitask learning. The input to the CNNs are time-frequency representations obtained from transitions between voiced and unvoiced segments. The evaluated tasks correspond to sub-scores of a full scale designed to assess the dysarthria deficits of the patients.

Table 6: *Comparison between multitask learning and single learning for the classification of PD vs. HC subject and the prediction of the m-FDA score.* ***Dev.****: results for the development set,* ***Test****: results for the test set.*

Task	Metric	Multitask			Single task		
		Dev.	Test	γ	Dev	Test	γ
PD vs. HC	ACC.	92.0	80.0	0.8	89.0	74.0	1
Total m-FDA	ρ	0.79	0.58	0.5	0.71	0.54	0

The multitask learning approach improves the generalization of the CNN, producing more representative feature maps to assess the different speech symptoms of PD patients. The results indicate that it is more suitable to train a CNN in a multitasks learning scheme rather than to train individual CNNs to learn tasks for each deficit of the PD patients. The most representative tasks in the multitask learning where those related to the articulation dimension of the speech, including those to assess the movement of the lips, tongue and larynx. This fact confirms the convenience of using information from the onset and offset transitions to model the articulatory capability in the speech of PD patients. An additional improvement in the results might be obtained if only those tasks related to the articulation capabilities are used in the multi-task learning framework. Other models might be considered in further experiments to assess and improve the results in the other tasks, which are not related to the articulation impairments such as respiration, monotonicity, and intelligibility.

6. Acknowledgements

The work reported here was financed by CODI from University of Antioquia by grants Number 2015–7683. This project has received funding from the European Unions Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie Grant Agreement No. 766287. Toms Arias-Vergara is under grants of Convocatoria Doctorado Nacional-785 financed by COLCIENCIAS.

7. References

[1] O. Hornykiewicz, "Biochemical aspects of Parkinson's disease," *Neurology*, vol. 51, no. 2 Suppl 2, pp. S2–S9, 1998.

[2] C. G. Goetz et al., "Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results," *Movement Disorders*, vol. 23, no. 15, pp. 2129–2170, 2008.

[3] J. A. Logemann, H. B. Fisher, B. Boshes, and E. R. Blonsky, "Frequency and cooccurrence of vocal tract dysfunctions in the speech of a large sample of Parkinson patients," *Journal of Speech and Hearing Disorders*, vol. 43, no. 1, pp. 47–57, 1978.

[4] J. Hlavnicka, R. Cmejla, T. Tykalova, K. Sonka, E. Ruzicka, and J. Rusz, "Automated analysis of connected speech reveals early biomarkers of parkinson's disease in patients with rapid eye movement sleep behaviour disorder," *Nature Scientific Reports*, vol. 7, no. 12, pp. 1–13, 2017.

[5] H. Ackermann and W. Ziegler, "Articulatory deficits in parkinsonian dysarthria: an acoustic analysis." *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 54, no. 12, pp. 1093–1098, 1991.

[6] J. R. Orozco-Arroyave, J. C. Vásquez-Correa *et al.*, "Neurospeech: An open-source software for Parkinson's speech analysis," *Digital Signal Processing (In press)*, 2017.

[7] A. Tsanas, M. A. Little, C. Fox, and L. O. Ramig, "Objective automatic assessment of rehabilitative speech treatment in Parkinson's disease," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 1, pp. 181–190, 2014.

[8] T. Grósz, R. Busa-Fekete *et al.*, "Assessing the degree of nativeness and Parkinsons condition using Gaussian processes and deep rectifier neural networks," in *Proceedings of INTERSPEECH*, 2015, pp. 1339–1343.

[9] J. C. Vásquez-Correa, J. R. Orozco-Arroyave, and E. Nöth, "Convolutional neural network to model articulation impairments in patients with Parkinson's disease," in *Proceedings of INTERSPEECH*, 2017, pp. 1–5.

[10] B. Schuller, S. Steidl *et al.*, "The INTERSPEECH 2015 computational paralinguistics challenge: Nativeness, Parkinson's & eating condition," in *Proceedings of INTERSPEECH*, 2015, pp. 478–482.

[11] M. Tu, V. Berisha, and J. Liss, "Interpretable objective assessment of dysarthric speech based on deep neural networks," in *Proceedings of INTERSPEECH*, 2017, pp. 1849–1853.

[12] M. Cernak *et al.*, "Characterisation of voice quality of Parkinsons disease using differential phonological posterior features," *Computer Speech & Language*, 2017.

[13] J. C. Vasquez-Correa, J. R. Orozco-Arroyave, T. Bocklet, and E. Nöth, "Towards an automatic evaluation of the dysarthria level of patients with parkinsons disease," *Journal of Communication disorders (To appear)*, 2018.

[14] J. R. Orozco-Arroyave, J. C. Vásquez-Correa, F. Hönig, J. D. Arias-Londoño, J. F. Vargas-Bonilla, S. Skodda, J. Rusz, and E. Nẗh, "Towards an automatic monitoring of the neurological state of parkinson's patients from speech," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2016, pp. 6490–6494.

[15] R. Caruana, "Multitask connectionist learning," in *Proceedings of the Connectionist Models Summer School*, 1994, pp. 372–379.

[16] T. Tieleman and G. E. Hinton, "Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude," *COURSERA: Neural networks for machine learning*, vol. 4, no. 2, pp. 26–31, 2012.

[17] J. Snoek, H. Larochelle, and R. P. Adams, "Practical bayesian optimization of machine learning algorithms," in *Advances in neural information processing systems (NIPS)*, 2012, pp. 2951–2959.

[18] P. M. Enderby and R. Palmer, *FDA-2: Frenchay Dysarthria Assessment: Examiner's Manual*. Pro-ed, 2008.

[19] J. R. Orozco-Arroyave *et al.*, "New Spanish speech corpus database for the analysis of people suffering from Parkinson's disease," in *Language Resources and Evaluation Conference, (LREC)*, 2014, pp. 342–347.