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UPDRS tracking using linear regression and neural network for Parkinson's disease prediction

Elmehdi BENMALEK[1], Jamal ELMHAMDI[2] , Abdelilah JILBAB[3]

[1,2,3] Laboratory LRGE, ENSET, Mohamed V University,
Rabat, Morocco

Abstract

The Unified Parkinson's Disease Rating Scale (UPDRS) is often used to track Parkinson's disease (PD) but it requires costly and logistically inconvenient for patient and clinical staff. In this work we present clinically useful accuracy replication of UPDRS, so we can classify the disease's severity of the patients with, and predict the evolution of PD based on those results. We map the features extracted from the speech to UPDRS using Least-squares regression technique and neural network. We applied our techniques on large database of PD speech (~6,000 recordings from 42PD patients). And we compare our results with state of the art.

Keywords: UPDRS tracking, Parkinson disease, linear regression, neural network.

1. INTRODUCTION

Neurological disorders affect people and claim lives at worldwide rate. Parkinson's disease (PD) is the second most common neurodegenerative disorder after Alzheimer's [1], because the population is growing older we expected to increase [2]. PD prevalence in men is greater than women and the lifetime risk [3] [4], considering current global average life expectancy, is estimated to be 4.4% (men) and 3.7% (women) [5]. Aging is associated with a number of detrimental effects on a person's health impinging on, amongst others, the nervous system. In fact, all studies suggest age is the single most important risk factor for the onset of PD, which increases steeply after age 50.

Speech disorders have been linked to PD [6] [7] [8], and with PD progression there is strong supporting evidence of degrading voice performance [9] [10]. Differentiating PWP (People with Parkinson) from healthy controls using speech has attracted interest in the research community [9] [11] [12] [13]. In this study we extend this concept to map the severity of voice-based PD symptoms to the Unified Parkinson's Disease Rating Scale (UPDRS).

Recent studies have raised the important topic of finding a statistical mapping between speech properties and UPDRS as an issue worthy of further investigation, but have not addressed it explicitly [14] [15]. The first studies that uses this concept to leads to clinically useful UPDRS estimation, and demonstrate remote PD monitoring was made by [16], which we took as reference to compare our results.

2. METHODS

The At-Home Testing Device (AHTD) database was described in [10], it is a novel telemonitoring device built by Intel Corporation for collecting data from PWP. The data [13] is collected at the patient's home, transmitted over the internet, and processed appropriately in the clinic to predict the UPDRS score. The description of the system used for recording can be found detailed in [16].

Figure 1 presents graphically the process of data acquisition and UPDRS estimation. The data is collected at the subject's home, transmitted by internet, and processed in the clinic to predict the UPDRS score.

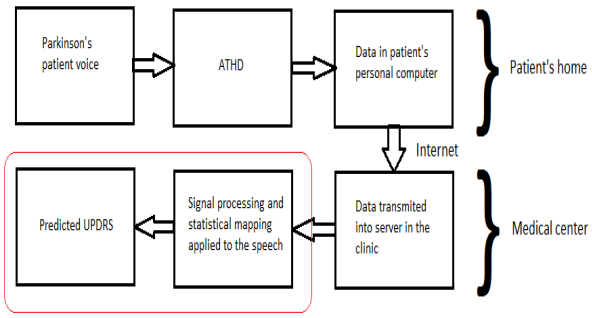

Fig. 1: Schematic diagram of the data acquisition procedure and the methodology to estimate the Parkinson's disease symptom severity, using the Unified Parkinson's Disease Rating Scale (UPDRS). The device that collects the data is known as the At-Home-Testing-Device (AHTD). The red box is the focus of this study.

Algorithms aiming to characterize clinically relevant properties from speech signals can be broadly categorized into classical linear and non-classical nonlinear methods [13], [17]-[19]. With the term linear we refer to a method where the output is proportional to a linear combination of the inputs; conversely, nonlinear methods have more general relationships between the inputs and the output. Here, we applied both methods linear and nonlinear.

This preliminary correlation analysis suggests that, taken individually, the dysphonia measures are weakly correlated to UPDRS [16]. Our aim is to maximally exploit the information contained in the combined dysphonia measures to produce a model that maximize the accuracy of UPDRS prediction. We used a linear and nonlinear regression methods to map the dysphonia

measures to interpolated UPDRS values, and compared their predictive performance. Linear regression methods assume that the regression function f(x) = y which maps the dysphonia measures x=(x1….xM) where M is the number of inputs to the UPDRS output y.

The linear techniques used were classical least squares (LS), and reduced model of input entries based on correlation described later. LS determines the coefficients b that minimize the residual sum of squares between the actual UPDRS and the predicted one. A problem often encountered in such regression methods when using a large number of input variables (16 in this case) is the curse of dimensionality: fewer input variables could potentially lead to a simpler model with more accurate prediction. Research has shown that many of the dysphonia measures are highly correlated (Table 1), so we can assume that taken together, highly correlated measures contribute little additional information for UPDRS prediction. Following the general principle of parsimony, we would like to reduce the number of measures in the analysis and still obtain accurate UPDRS prediction. It may well be the case that the dysphonia measures do not combine linearly to predict the UPDRS. Thus, nonlinear regression may be required, where the prediction function f(x) is a nonlinear combination of the inputs x. To test this idea, we used a neural network that updates weight and bias values according to Levenberg-Marquardt optimization [20] [21]. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training.

3 RESULTS

The exploration of the data is done by computing the relevance of speech features to UPDRS. Speech appears explicitly in two sections of the UPDRS, which can be combined to form the 'speech-UPDRS' quantity indicating strong association between speech and UPDRS [22]

3.1 Linear regression

Table 1 presents the Spearman rank-correlation between all the dysphonia measures. All measures were significantly correlated. We used those results to test linear regression with reduced entries.

Table 1: The correlation columns are the Spearman non-parametric correlation coefficients ρ between two measures. Bold italic entries indicate high correlation between measures (Spearman $\rho \geq 0.95$).

	Jitter (%)	Jitter (Abs)	Jitter RAP'	Jitter PPQ 5	Jitter DDP	Shimmer	Shimmer (dB)	Shimmer (APQ3')	Shimmer (APQ5')	Shimmer (APQ11')	Shimmer (DDA')	NHR'	HNR'	RPDE	DFA
Jitter (Abs)	0.86														
Jitter: RAP'	**0.98**	0.84													
Jitter: PPQ5	**0.97**	0.79	**0.95**												
Jitter: DDP'	**0.98**	0.84	**1.00**	**0.95**											
Shimmer'	0.71	0.65	0.68	0.73	0.6817										
Shimmer (dB	0.72	0.65	0.68	0.73	0.69	**0.99**									
Shimmer: APQ3'	0.66	0.62	0.65	0.68	0.65	**0.98**	**0.97**								
Shimmer: APQ5'	0.69	0.62	0.66	0.73	0.66	**0.98**	**0.98**	**0.96**							
Shimmer: APQ11'	0.64	0.59	0.60	0.67	0.60	0.9355	0.93	0.88	0.94						
Shimmer: DDA'	0.66	0.62	0.65	0.68	0.65	**0.98**	**0.97**	**1.00**	**0.96**	0.88					
NHR'	0.82	0.70	0.79	0.86	0.79	0.80	0.80	0.73	0.78	0.71	0.73				
HNR'	-0.67	-0.71	-0.64	-0.66	-0.64	-0.80	-0.80	-0.78	-0.79	-0.78	-0.78	-0.68			
RPDE'	0.43	0.55	0.38	0.38	0.33	0.47	0.47	0.44	0.45	0.48	0.44	0.42	-0.76		
DFA'	0.23	0.35	0.21	0.17	0.21	0.13	0.12	0.13	0.13	0.18	0.13	-0.02	-0.66	0.19	
PPE'	0.72	0.79	0.67	0.66	0.67	0.61	0.63	0.58	0.59	0.62	0.58	0.56	-0.29	0.57	0.39

Table 2 presents the regression coefficient values calculated for the linear predictionof the all dysphonia measures of one patient.

Table 2: the regression coefficient of the all dysphonia measures of one patient.

Features	Coefficients de regression
Jitter (%)	-3634,28807802494
Jitter(Abs)	405670,165940963
Jitter:RAP’	-223528,509994944
Jitter:PPQ5	-3643,97032029276
Jitter:DDP’	75818,6481002305
Shimmer’	-202,797380135604
Shimmer(dB	-24,9750730850773
Shimmer:APQ3’	-181446,156909467
Shimmer:APQ5’	-348,077989534102
Shimmer:APQ11’	563,319185452980
Shimmer:DDA’	60652,7486077727
NHR’	78,1328439682353
HNR’	0,398658012743896
RPDE’	-23,9436557355571
DFA’	50,4107770136425
PPE’	35,3679900585830

3.2Neural network

The type of the neural network used is a feedforward neural network, which is an artificial neural network where connections between the units do not form a directed cycle. This is different fromrecurrent neural networks. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network.For the prediction by neural network the input vectors and target vectors will be randomly divided into three sets as follows: 75% for training, 15% will be used to validate that the network is generalizing and to stop training before overfitting, the last 10% will be used as a completely independent test of network generalization, for the hidden neurons we used 25.

3.3 The results

The difference between predicted and linearly interpolated UPDRS values is typically low.The table 3 shows comparison between the different methods, the first is a linear regression with all the 16 dysphonia measures, the second with only 5 dysphonia measures, and last one using neural network.

Table 3: Comparison of UPDRS calculated using the 3 methods proposed

UPDRS Réel	Least-squares regression (All features)	Least-squares regression (5 selected features)	Neural network
28.199	29,1549349220268	28,9836977556020	28,5317421231019
28.447	32,1028863140254	31,8048296893530	32,6003910409079
28.695	30,7178686947591	29,1028944591480	30,9660958803975
28.905	34,0468863640356	33,5093521686119	32,4083021154767
29.187	31,8246339360839	31,8298516957525	32,4136772108248
29.435	33,3736382177836	29,7878875048577	31,8570661933224
29.682	30,9149891519664	32,5843219273534	30,1972789004171
29.928	29,7350318661620	30,0448744358009	29,5856854555382
30.177	33,6701648295743	32,5361708481412	32,1984285139203
30.424	33,2230329399721	31,8765751189306	33,3383233813939
30.67	33,1609264307126	31,8273715126340	33,5042075183861
30.917	31,2584829080419	31,3534555124748	31,9396524720400
31.309	33,9581978651781	30,0738281972529	31,9282922057661
31.776	29,1549349220268	30,3384729873161	33,7065002958403
32.243	32,1028863140254	31,7140355933814	34,3566876944685
32.71	30,7178686947591	29,6226385003943	33,7067237856772
33.178	34,0468863640356	31,0280297811787	33,2864472300403
33.643	31,8246339360839	28,9836977556020	32,7108175193045
34.109	33,3736382177836	31,8048296893530	32,3703189158198
34.646	30,9149891519664	29,1028944591480	32,7823744635445
35.043	29,7350318661620	33,5093521686119	32,3770284716834
35.509	33,6701648295743	31,8298516957525	33,6374700835770
35.976	33,2230329399721	29,7878875048577	32,2093301775492
36.977	33,1609264307126	32,5843219273534	33,7425736047769

As the results shown in table 3 of the UPDRS tracking of the patient throughout the six-month trial for the linearmethods and neural network. We conclude that neural network achieves the best prediction with the smallest prediction error.

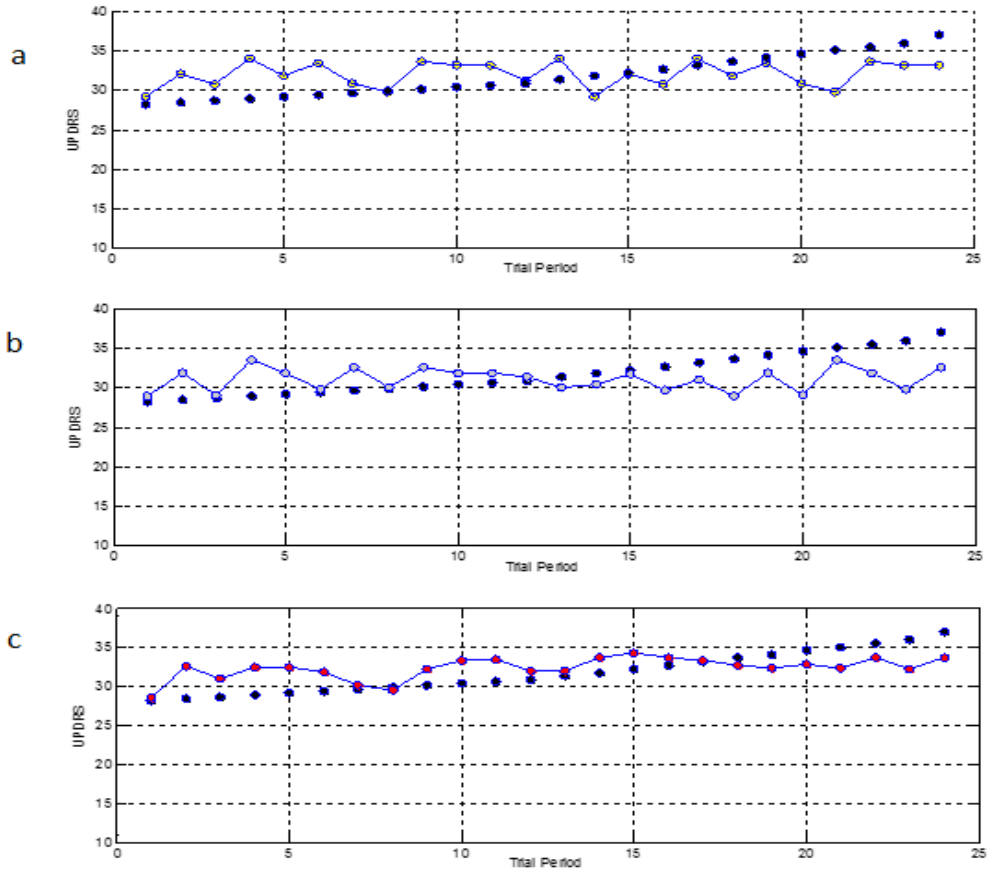

Fig 2: UPDRS tracking of the 6 months trial period for patient: a) linear regression, b) reduced model using linear regression, c) neural network. The black dots denote the piecewise linearly interpolated UPDRS, and the colored one for the predicted UPDRS

Figure2 presents the UPDRS tracking of a PWP using the methods described in this work. We remark that the proposed models replicate quite accurately the UPDRS scores. The Least-squares regression gives a good results with 5.3 points as error which is useful in clinical staff, for the linear model with reduced entries we got 6.2 points of error, considered good results of value, finally the neural network has the less error with 4.2 points.

4.Conclusion

This study investigated the potential of using speech signal analysis to replicate PD symptom severity as defined by the standard reference clinical metric Unified Parkinson‘s Disease Rating Scale (UPDRS).

It has been demonstrated that the UPDRS can be estimated within approximately 4.2 points compared to 7.5 points found in previous researches [16].

In a general statistical regression setting, some variables (here the dysphonia measures) will be mapped to a target variable (here UPDRS). Linear regression is a simple and often adequate approach, token as a benchmark against which more complicated nonlinear regression methods to be compared with. Some of the dysphonia measures are highly correlated with each other, which suggested the removal of those measures, and we still get useful UPDRS scores.

We believe these results could be of value in clinical trials, presenting clinical staff with a useful guide to clinical rater tracking of PD symptoms by UPDRS.

References

[1] M.C. de Rijk et al. Prevalence of Parkinson’s disease in Europe: a collaborative study of population-based cohorts. Neurology, Vol. 54, pp. 21–23, 2000

[2] S.K. Van Den Eeden et al.. Incidence of Parkinson’s disease: Variation by age, gender, and Race/Ethnicity. Am J Epidem 157, 1015-1022, 2003

[3] M. Baldereschi, A. De Carlo, W.A. Rocca et al., Parkinson‘s disease and parkinsonism in a longitudinal study. Two fold higher incidence in men,|| Neurology, Vol. 55, pp. 1358-1363, 2000

[4] C.A. Haaxma, B.R. Bloem, G.F. Borm, et al., Gender differences in Parkinson‘s disease, Journal of Neurologie, Neurosurgey and psychiatry Vol 78, 2007

[5] Neurology,‖ Neurosurgery and Psychiatry, Vol. 78, pp. 819-824, 2007
[6] A. Elbaz et al. Risk tables for Parkinsonism and Parkinson's disease. Journal of Clinical Epidemiology. Vol. 55, pp. 25-31, 2002
[7] F.L. Darley, A. E. Aronson and J. R. Brown, ―Differential diagnostic patterns of dysarthria,‖ Journal of Speech and Hearing Research, Vol. 12, pp. 246-269, 1969
[8] J. Gamboa, F.J. Jimenez-Jimenez, A. Nieto, J. Montojo, M. Orti-Pareja, J.A. Molina, E. Garcia-Albea, I. Cobeta, ―Acoustic voice analysis in patients with Parkinson'sdisease treated with dopaminergic drugs,‖ Journal of Voice, Vol. 11, pp. 314-320, 1997
[9] A. Ho, R. Iansek, C. Marigliani, J. Bradshaw, S. Gates. Speech impairment in a large sample of patients with Parkinson's disease. Behavioral Neurology 11, 131-37, 1998
[10] B. Harel, M. Cannizzaro and P.J. Snyder. Variability in fundamental frequency during speech in prodromal and incipient Parkinson's disease: A longitudinal case study, Brain and Cognition 56, 24–29, 2004
[11] S. Skodda, H. Rinsche, U. Schlegel. Progression of dysprosody in Parkinson's disease over time – A longitudinal study. Movement Disorders 24 (5), 716-722, 2009
[12] S. Sapir, J. Spielman, L. Ramig, B. Story, C. Fox. Effects of Intensive Voice Treatment (LSVT) on Vowel Articulation in Dysarthric Individuals with Idiopathic Parkinson Disease: Acoustic and Perceptual Findings. J. Speech, Lang. Hear Research , Vol.50, pp. 899-912, 2007
[13] L. Cnockaert et al. Low frequency vocal modulations in vowels produced by Parkinsonian subjects, Speech Comm 50, 288-300, 2008
[14] M.A. Little, P.E. McSharry, E.J. Hunter, J. Spielman, L.O. Ramig. Suitability of dysphonia measurements for telemonitoring of Parkinson's disease, IEEE Trans. Biomedical Engineering 56(4), 1015-1022, 2009
[15] C.G. Goetz. et al. Testing objective measures of motor impairment in early Parkinson's disease: Feasibility study of an at-home testing device. Movement Disorders 24 (4), 551-556, 2009
[16] C.G. Goetz, G.T. Stebbins, D. Wolff, W. DeLeeuw, H. Bronte-Stewart, R. Elble, M. Hallett, J. Nutt, L. Ramig, T. Sanger, A.D. Wu, P.H. Kraus, L.M. Blasucci, E.A. Shamim, K.D. Sethi, J. Spielman, K. Kubota, A.S. Grove, E. Dishman, C.B. Taylor, ―Testing objective measures of motor impairment in early Parkinson's disease: Feasibility study of an at-home testing device,‖ Movement Disorders, Vol. 24 (4), pp. 551-556, 2009
[17] Tsanas, A., Little, M., McSharry, P. E., & Ramig, L. O. (2010). Accurate telemonitoring of Parkinson's disease progression by noninvasive speech tests. *Biomedical Engineering, IEEE Transactions on*, *57*(4), 884-893
[18] P. Boersma and D. Weenink: Praat: doing phonetics by computer [Computer program]. Retrieved from http://www.praat.org/, 2009
[19] M.A. Little. Biomechanically Informed Nonlinear Speech Signal Processing, DPhil Thesis, University of Oxford, Oxford, UK, 2007
[20] M.A. Little, P.E. McSharry, S.J. Roberts, D. Costello, I.M. Moroz. Exploiting Nonlinear Recurrence and Fractal Scaling Properties for Voice Disorder Detection. Biomedical Engineering Online 6:23, 2007
[21] Levenberg, K. "A Method for the Solution of Certain Problems in Least Squares." Quart. Appl. Math. 2, 164-168, 1944.
[22] Marquardt, D. "An Algorithm for Least-Squares Estimation of Nonlinear Parameters." SIAM J. Appl. Math. 11, 431-441, 1963
[23] Tsanas, A., Little, M. A., McSharry, P. E., & Ramig, L. O. (2011). Nonlinear speech analysis algorithms mapped to a standard metric achieve clinically useful quantification of average Parkinson's disease symptom severity. Journal of the Royal Society Interface, 8(59), 842-855.