Prosodic production in right-hemisphere stroke patients: using temporal dynamics to characterize voice quality

Ethan Weed[1,2,3], Riccardo Fusaroli[2,3,4]

[1] Linguistics, Aarhus University, [2] Interacting Minds Center, Aarhus University, [3] Center of Functionally Integrative Neuroscience, Aarhus University, [4] Center for Semiotics, Aarhus University,

Introduction

Brain injury to the right hemisphere can result in impaired communication, despite relatively well-preserved core linguistic skills. Impaired ability to produce a normal prosodic intonation has been reported (Duffy, 2012).

The purpose of this project was to expand on traditional acoustic measures to refine our understanding of RHD prosody. Our aims were:

1) to achieve a more **fine-grained understanding of the speech patterns in RHD** than has previously been achieved using traditional acoustic measures
2) to use supervised machine-learning to **classify speech production** as belonging to the control or the RHD group
3) **assess symptoms' severity** based solely on voice dynamics.

Materials & Methods

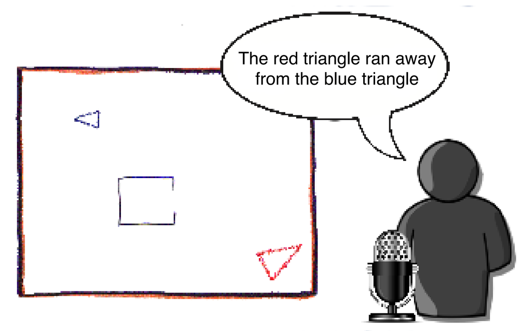

Figure 1

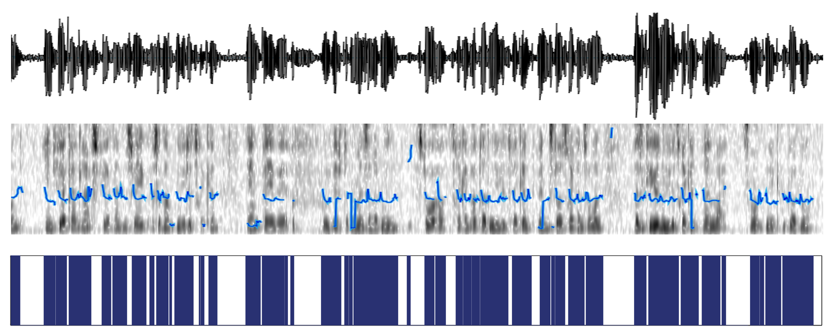
Figure 2

Our analyses were based on previously collected descriptions of the Frith-Happé triangles (Abel et al, 2000) by 21 participants (11 patients with RHD, 8F and 3M, mean age=63, sd=8 and 10 matched controls) for a total of 151 video descriptions.

We selected basic measures of pause behavior (Number of Pauses, Average Length) and fundamental frequency (Fig 2). (Minimum, Maximum, Mean and Range) as well as measures of stability and regularity for both (Recurrence Rate, Det, L, LMax, Entr, Lam, Vmax, T1, T2, Trend) (Fig 3). In all cases we employed ElasticNet (10-fold cross-validation, Alpha=.5) to further limit the number of features selected.

Materials & Methods (Cont'd)

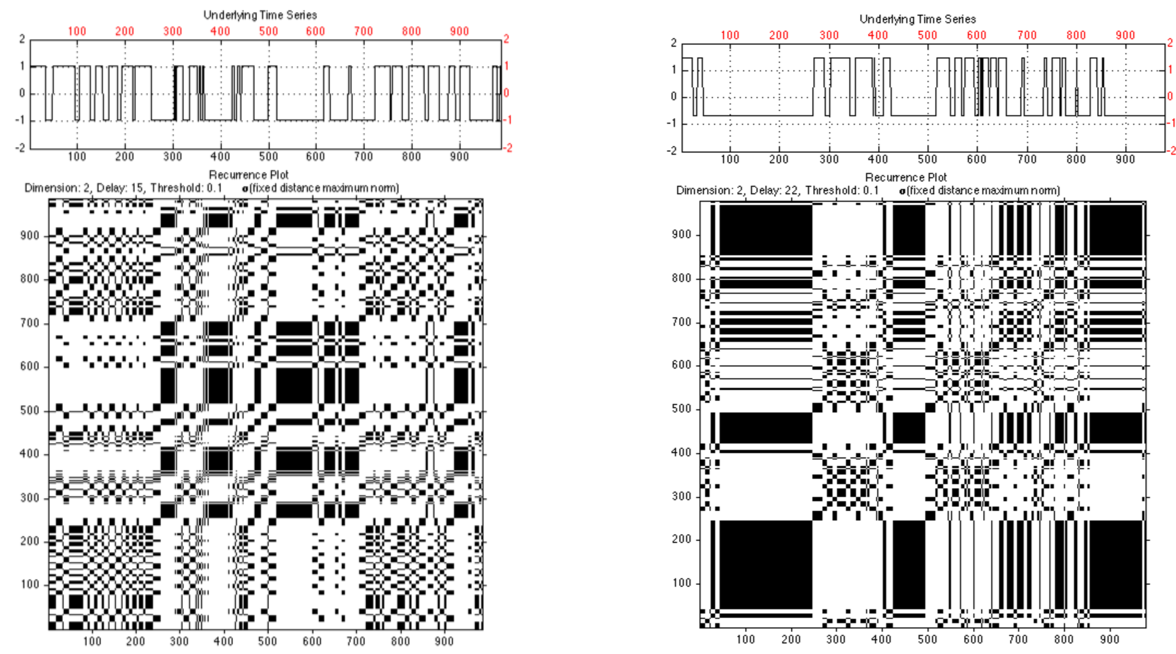
Figure 3

We employed a 10-fold cross-validated discriminant function (Mahalanobis rule), and a 10-fold cross-validated logistic regression to classify the selected features. We then used a 10-fold cross-validated multiple linear regression to predict scores on the FIM. The variance explained is balanced by individual variability and number of predictors. The classification and regression processes were iterated 1000 times and the results averaged.

Results

Diagnosis based on voice quality was good, with an average **balanced accuracy of 88.43 %** ($p<.00001$, confidence intervals: 83.5-92.36 percent). Sensitivity was 89.6%, and specificity was 96.75%.

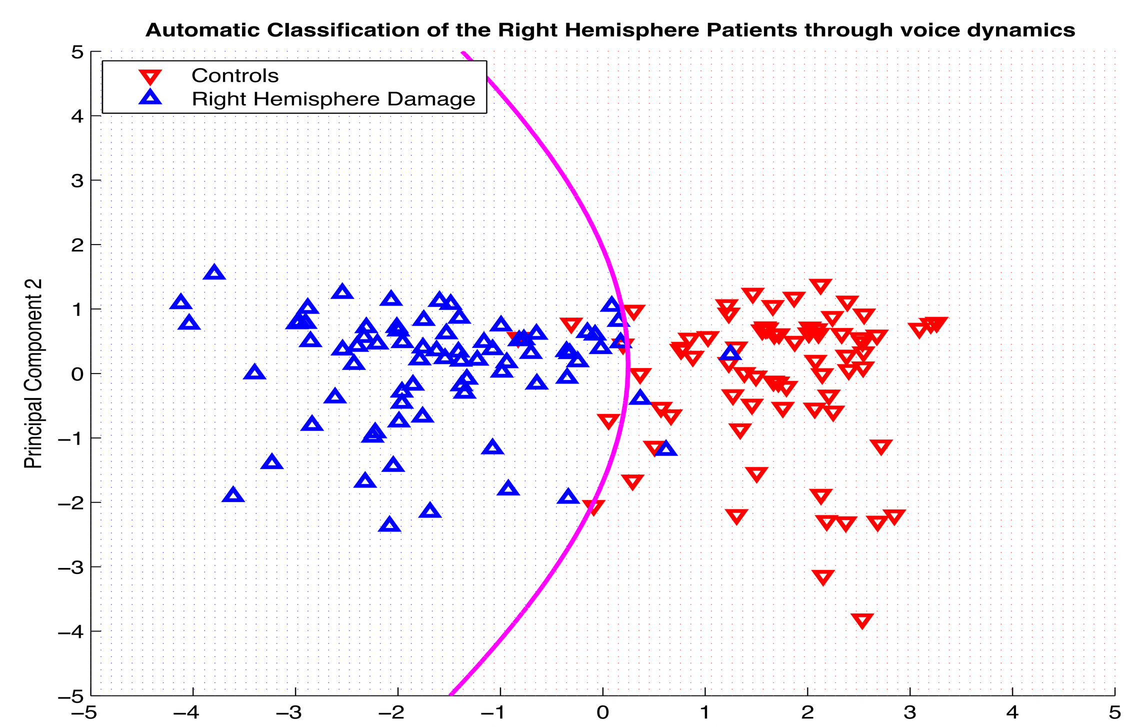

Figure 4

Results (Cont'd)

Prediction of FIM scores was also good, with an **adjusted R square of 70.80% (p< .00001).** The voice of participants with RHD was characterized by **long and frequent pauses**, as well as by a **low speech rate**. F0 was less varied and organized in longer repeated sequences grouped in shorter cycles.

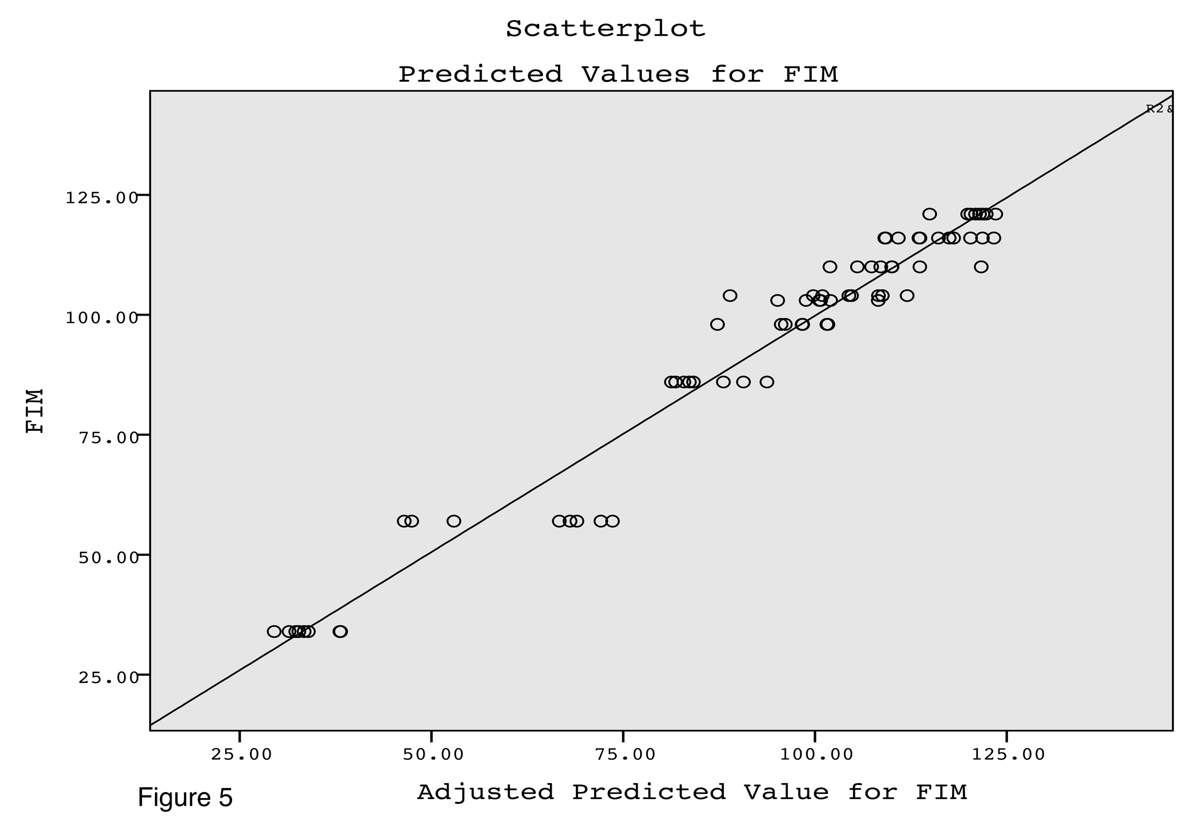

Figure 5

Conclusion

RHD productions could be automatically "diagnosed" by a classifier, using few acoustic features. In addition, these features could reliably predict functional indepenence measures

References

Abel, F., Happé, F., & Frith, U. (2000) Do triangles play tricks? Attribution of mental states to animated shapes in normal and abnormal development. Journal of Cognitive Development 15(1), 1-16

Boersma, Paul (2001). Praat, a system for doing phonetics by computer. Glot International 5:9/10, 341-345.

Duffy, Joseph R. (2012). Motor speech disorders: Substrates, Differential Diagnosis, and Management, 3rd. edition. St. Louis: Elsevier.

Fusaroli, Riccardo, Tylén, Kristian, Simonensen, Arndis, Weed, Ethan (2013). Non-linear dynamics of speech and voice in schizophrenia. Poster presented at Cognitive Science, Berlin.

Marwan, N., Carmen Romano, M., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. Physics Reports, 438(5-6), 237-329

Rodriguez, J. D., Perez, A., & Lozano, J. A. (2010). Sensitivity analysis of k-fold cross validation in prediction error estimation. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 32(3), 569-575.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 67(2), 301-320