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# Automatic Anomaly Detection for Dysarthria Across Two Speech Styles: Read vs Spontaneous Speech

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## Abstract

Perceptive evaluation of speech disorders is still the standard method in clinical practice for the diagnosing and the following of the condition progression of patients. Such methods include different tasks such as read speech, spontaneous speech, isolated words, sustained vowels, etc. In this context, automatic speech processing tools have proven pertinence in speech quality evaluation and assistive technology-based applications. Though, a very few studies have investigated the use of automatic tools on spontaneous speech. This paper investigates the behavior of an automatic phone-based anomaly detection system when applied on read and spontaneous French dysarthric speech. The behavior of the automatic tool reveals interesting inter-pathology differences across speech styles.

**Keywords:** Dysarthria, automatic speech processing, anomaly detection, read speech, spontaneous speech, speech disorders

## 1. Introduction

Dysarthria is a motor speech disorder resulting from neurological damages located either in the central or in the peripheral nervous system. This may lead to disturbances in any of the components involved in the speech production, including respiratory, phonatory, resonatory, articulatory and prosodic elements. Consequently, this may be reflected by weakness, spasticity, incoordination, involuntary movements, or abnormal muscle tone, depending on the location of the neurological damage. Dysarthric speech has been studied according to different axes : perceptual evaluation of speech alterations for dysarthria classification (Darley et al., 1969; Duffy, 2005; Darley et al., 1975), different speech tasks (Van Lancker Sidtis et al., 2012; Kempler and Van Lancker, 2002), perceptual measurement of dysarthria severity, notably related to the speaker's intelligibility (Enderby, 1983; Yorkston et al., 1996; Hustad, 2008; Lowit and Kent, 2010) or articulatory or/and acoustic analysis (Kent et al., 1999; McAuliffe et al., 2006; Rosen et al., 2006; Green et al., 2013; Whitfield and Goberman, 2014) in order to observe and characterize the effects of dysarthria in the speech signal. These studies aim at helping clinicians in their knowledge of the speech impairment and its clinical evaluation, crucial for following the condition progression of patients in the case of treatment or/and of speech rehabilitation to enhance them.

In this context, automatic speech processing approaches have been seen, very early, as potential solutions to provide objective tools to deal with speech disorders (Ferrier et al., 1992; Rosen and Yampolsky, 2000; Carmichael, 2007; Middag et al., 2009; Nuffelen et al., 2009; Kim and Kim, 2012). In addition, they can also help people with speech disorders in their everyday life through Alternative and Augmented Communication (AAC) tools, involving automatic speech recognition for instance (Green et al., 2003; Parker et al., 2006; Rudzicz et al., 2012; Christensen et al., 2013a; Christensen et al., 2013b).

In the literature, the set of acoustic-perceptual cues including imprecision of consonants, distortion of vowels,

slow rate, monopitch, monoloudness, hypernasality is commonly used to characterize the main disturbances of the various types of dysarthria in the speech production. But, more descriptive acoustic and phonetic analyses are still necessary to take into account the large variability in terms of speech alterations observed among people in different groups of diseases, within the same group (Tomik and Guiloff, 2010) or across different speech styles (read speech, spontaneous speech, singing, isolated words, etc). Moreover, so that such analyses are relevant, they require a large number of people with speech disorders, a variety of diseases related to the different types of dysarthria (spastic, flaccid, ataxic, hyper- or hypokinetic, unilateral upper motor neuron, or mixed), various levels of condition progression and of severity degree in order to observe their effects on the speech production as well as the possible compensation strategies set up by speakers. Still here, automatic speech processing approaches would be of major interest in the task of focusing the attention of human experts on specific speech segments (among a large amount of speech productions) exhibiting unexpected acoustic patterns compared with a normal speech production.

As reported in (Chandola et al., 2007) in a more general context, anomaly detection refers to the problem of finding patterns in data that do not conform to an expected behavior. In dysarthric speech, anomalies can refer to the unexpected acoustic patterns mentioned above and observed at different units of speech like phones for instance.

In previous works (Fredouille and Pouchoulin, 2011; Laaridh et al., 2015a), the authors have proposed an automatic phone-based anomaly detection approach in two steps : a text-constrained phone alignment to obtain the phone segmentation and a classification of speech segments into normal and abnormal phones (anomalies). Furthermore, in (Laaridh et al., 2015b), the quality of the automatic phone alignment was studied and found to be depending on phonetic categories, pathologies and the severity of the dysarthria. In this paper, the authors investigate the impact of the speech styles on the automatic anomaly detection and

classification process, focusing on read and spontaneous speech. Indeed, comparative studies on motor speech disorders have found different articulatory and voice characteristics (for instance speech rate and breath-pause positions (Brown and Docherty, 1995)) between speech styles. Also, it could be expected that dysarthric speakers develop strategies to avoid "difficult" linguistic contexts. Such strategies could only be applied during spontaneous speech. Within this context, it is interesting to study whether our classification system is able to detect anomalies in spontaneous speech and whether it has the same behavior as when facing read dysarthric speech. This study is conducted in the context of French dysarthric speech produced by people suffering from four different pathologies.

The rest of this paper is organized as follows. In section 2, both steps of the automatic anomaly detection approach are described. The corpora used in this study are presented in section 3. In section 4, the behavior of the approach facing both read and spontaneous speeches is compared and discussed. Finally, section 5 provides a conclusion and directions for future works.

## 2. Automatic Anomaly Detection

The anomaly detection approach studied here relies on two steps. The first step is a text-constrained phone alignment. The second step consists of a two class (normal and abnormal phones) supervised classification. In each class, phones are characterized by a set of features considered as relevant for the discrimination task.

### 2.1. Automatic Phone-based Alignment

The segmentation of speech utterances into phones is carried out thanks to an automatic text-constrained phone alignment tool. This tool takes as input the sequence of words pronounced in each utterance and a phonetized phonologically-varied lexicon of words based on a set of 37 French phones. The sequence of words comes from a manual orthographic transcription performed by a human listener following some annotation rules. For this manual transcription, inter-pausal units (IPUs) are annotated by the human listener. An IPU is defined as a pause-free unit of speech separated from another IPU by at least 250ms of silence or non-speech. The automatic alignment process is then based on a Viterbi decoding and graph-search algorithms, the core of which is the acoustic modeling of each phone, based on a Hidden Markov Model (HMM). In this work, each phone is modeled using a 3-state context-independent HMM topology which are built using the Maximum Likelihood Estimate paradigm on the basis of about 200 hours of French radiophonic speech recordings (Galliano et al., 2005). In order to get speaker-dependent models, a three-iteration Maximum A Posteriori (MAP) adaptation is performed to adapt all the HMM parameters. This automatic alignment process results in a couple of start and end boundaries per phone produced in the speech recordings.

### 2.2. Normal And Abnormal Speech Classification

This step aims at characterizing each phone with a set of features found to be relevant for the anomaly detection task. The set of features used is mainly derived from the automatic text-constrained phone alignment outputs. For each phone  $p$  and its associated speech segment  $y_p$ , the following features and acoustic scores are extracted:

- the phone duration, expressed in terms of the number of 10ms frames covered by  $y_p$ ;
- the number of frames in  $y_p$  for which the one-best state search among the HMM-based phone models, applied at the frame level, corresponds to those of  $p$ ;
- the acoustic score of the best matching phone  $p'$ , obtained by computing the scores of all the HMM phone models on segment  $y_p$ ; if  $p$  is the best matching phone, the second-best matching phone is considered instead;
- the phonetic category of  $p'$ ;
- the acoustic score of the second-best matching phone  $p''$ ; if  $p$  is one of the two best matching phones, the third one is considered instead;
- the phonetic category of  $p''$ ;
- the acoustic score of  $p$  and its rank compared to the scores of all the HMM phone models.

The classification task is based on Support Vector Machines (SVM), which have been largely applied to pattern recognition problems (Vapnik, 1995)(Scholkopf and Smola, 2001). Here, the SVM classification method is applied to a two-class problem: discriminating between normal and abnormal phones (anomalies). Each phone is characterized with the set of features defined above. All the SVMs are used with a polynomial kernel.

In order to better take into account each phonetic category specificities and to refine abnormal and normal classes, different SVM models are trained by distinguishing the speech productions by gender and phonetic categories (unvoiced consonants, voiced consonants, oral vowels, nasal vowels). The different SVM models are trained using the SVMlight tool (see (Joachims, 1999) for more information).

## 3. Corpora

The current study is based on two speech corpora.

Table 1: Information related to the LSD-corpus used in the modeling process including the # of speakers, the # of recordings and the minimum and maximum Dysarthria Severity Degrees (DSD) per disease.

Disease	# of speakers	# of recordings	(Min;Max) DSD
LSD	8	35	(1.5;3.0)
Control	6	17	-

Table 2: Information related to the TYPALOC corpus including the # of speakers, the average Dysarthria Severity Degrees (DSD) and the average and (Min;Max) of recording duration (sec.) and # of phones from the automatic alignment per disease and speech style.

Disease	# of speakers	Read speech			Spontaneous speech		
		Avg. DSD	Avg. dur. (Min;Max)	Avg. # of phones (Min;Max)	Avg. DSD	Avg. dur. (Min;Max)	Avg. # of phones (Min;Max)
ALS	12	2.0	111 (65;214)	532 (382;578)	2.0	102 (45;317)	463 (184;1089)
PD	8	0.8	74 (48;122)	567 (550;599)	1.0	65 (40;109)	365 (315;404)
CA	8	1.3	107 (73;142)	569 (544;595)	1.2	78 (40;124)	423 (223;838)
Control	12	-	70 (56;82)	558 (552;568)	-	522 (296;1028)	4072 (2762;7104)

The first corpus (LSD-corpus) contains 8 dysarthric speakers and 6 control subjects. The dysarthric speakers had been diagnosed with rare Lysosomal Storage Diseases (LSD), resulting in a mixed dysarthria, and showed disparities in the Dysarthria Severity Degree (DSD). All the speakers were asked to read the same text, a French fairytale called “Le cordonnier” (The cobbler), as naturally as possible and they each recorded 3 to 6 longitudinal records approximately every six months. All the speech utterances were annotated by a human expert in order to identify acoustic anomalies at the phone level. Consequently, this corpus was involved in the estimate of the normal and abnormal models required in the classification step described in section 2.2.. Table 1 provides information on this corpus.

The second corpus, named TYPALOC (Meunier et al., 2016), contains 28 dysarthric speakers and 12 control subjects. Each speaker read the same text as the LSD-corpus and made an additional spontaneous speech record. For both dysarthric and control speakers, the spontaneous speech situation was an interview conducted by a researcher/clinician in which they had to talk about their everyday life, personal history or even particular events. Unlike the first corpus in which only LSD patients were recorded, this corpus presents various diseases and types of dysarthria: Amyotrophic Lateral Sclerosis (ALS)/mixed dysarthria, Parkinson’s Disease (PD)/hypokinetic dysarthria and Cerebellar Ataxia (CA)/ataxic dysarthria distributed over various DSDs. All the patient’s speech recordings were evaluated perceptually by a jury of 11 experts who were asked to rate each patient on perceptual items of speech quality. Among these items, we focus on the DSD rated on a scale of 0 to 3 (0 -no dysarthria, 1 -mild, 2 - moderate, 3 -severe dysarthria). Table 2 provides information on the TYPALOC corpus grouped per pathology and speech style. This includes the number of patients, the average values of the DSD and the average and (Min;Max) of recording duration (sec.) and number of phones in the automatic alignment per speaker within each population.

We can point out that the spontaneous speech productions are shorter (duration and # of phones) than the read speech productions independently of pathologies. Indeed, patients are usually less prone to talk spontaneously due, not only to their pathologies and the fatigue effect, but also to the speech elicitation techniques used, which are not always fully adapted to this kind of speakers.

## 4. Results And Discussions

This section details and discusses the behavior of the automatic anomaly detection approach for both read and spontaneous speech on the TYPALOC corpus.

As reported in (Laaridh et al., 2015a) on read speech, the approach tends to detect more anomalies on patients with severe dysarthria. This behavior, though less distinct, seems preserved on spontaneous speech. Indeed, the correlation between the automatic anomaly rates and the DSD reaches 0.81 and 0.60 for read and spontaneous speech respectively. Similarly, figure 1 depicts the automatic anomaly rates for both read and spontaneous speech according to the patients’ DSD rated on the read speech uniquely (this typical configuration permits to locate anomaly rates for both read and spontaneous speech for each speaker more easily). This confirms that the system is able to detect the evolution of dysarthria regardless of the production task performed by the patients (read or spontaneous speech).

Table 3: Average anomaly rate (%) per pathology and speech style computed over all phones.

Disease	Read speech	Spontaneous speech
ALS	35.8	31.9
PD	10.6	17.8
CA	20.6	24.4
Control	5.4	13.7

In a more detailed way, table 3 reports automatic anomaly detection rates on read and spontaneous speech grouped by population.

First, We observe that over the control speakers, the approach detects more anomalies over spontaneous speech compared to read speech. This could be related to the fact that our models of normal and abnormal phones (section 2.2.) were built over read speech only. Indeed, spontaneous speech may present more acoustic variability that is atypical (compared to read speech) without being pathological. This variation may be due to faster speech rate, false starts, hesitations and phone reductions more frequent in spontaneous speech. Figure 2 depicts the relation between the read speech DSD and the difference of automatic anomaly detection rates between spontaneous and read speech (anomaly rate over spontaneous speech –



Table 4: Average automatic anomaly rate (%) computed per pathology, phonetic category and speech style (read and spontaneous speech).

Phonetic category	Read speech				Spontaneous speech			
	Control	PD	CA	ALS	Control	PD	CA	ALS
Plosives	7	12	22	37	11	16	24	35
Fricatives	7	26	48	37	23	55	53	38
Nasal consonants	7	12	21	31	19	10	19	35
Liquid consonants	7	9	23	41	15	9	27	44
Oral vowels	2	6	10	33	11	10	13	29
Nasal vowels	4	8	20	44	8	13	13	26
Other	10	16	26	46	19	13	26	37

of anomaly rates observed over ALS patients in table 3 between read and spontaneous speech is the result of the decrease observed over vowels since consonants maintain similar anomaly rates between both speech styles.

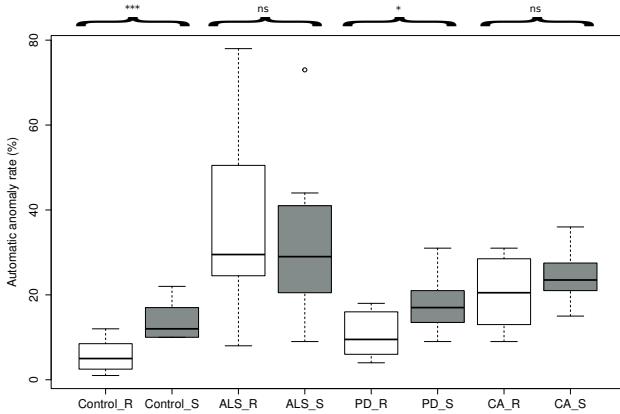


Figure 3: Box plot of automatic anomaly rate per population and speech style.

For each population, a one-way ANOVA was conducted in order to test the effect of speech style (2 levels: read speech, spontaneous speech). Figure 3 depicts the box plot representation of automatic anomaly rates for each population and speech style. For control and PD speakers, significant differences are found between read and spontaneous speech ( $p < 0.001, F(1,22)=28$ ) and ( $p < 0.05, F(1,14)=5.4$ ) respectively). These differences are emphasized when focusing only on fricatives ( $p < 0.001, F(1,22)=19$ ) and ( $p < 0.01, F(1,14)=14$ ) for control and PD speakers respectively). The difference between both speech styles is less distinct for patients suffering for CA and ALS. Indeed, the speech style effect can be masked by the higher intra-pathological variability observed over both populations unlike patients suffering from PD, having all a mild dysarthria.

## 5. Conclusion

The study of the behavior of an automatic phone-based anomaly detection system over read and spontaneous dysarthric speech has shown different effects of the task and the speech style according to pathologies. ALS patients, in contrast to all other populations (control, PD, CA),

showed more anomalies over read speech than spontaneous speech. Globally, the control speakers show the most important differences according to the speech style. Considering patients, the more severe the dysarthria is, the less difference between styles there is. A hypothesis could be that control speakers adapt their productions according to the speech style whereas dysarthric patients tend to gradually loose this capacity. By comparing the phonetic categories, fricatives show an important increase in terms of anomaly rates on spontaneous speech compared to read speech compared over the control speakers and the patients suffering from PD.

Future work will examine the effect of the localization of the phones (first, second, etc. syllable) on the anomaly detection process in order to investigate further on these different behaviors.

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## 7. Bibliographical References

- Brown, A. and Docherty, G. J. (1995). Phonetic variation in dysarthric speech as a function of sampling task. *International Journal of Language & Communication Disorders*, 30(1):17–35.
- Carmichael, J. (2007). *Introducing objective acoustic metrics for the Frenchay Dysarthria Assessment procedure*. Ph.d. dissertation, university of sheffield.
- Chandola, V., Banerjee, A., and Kumar, V. (2007). *Anomaly detection: a survey*. University of Minnesota (USA).
- Christensen, H., Green, P., and Hain, T. (2013a). Learning speaker-specific pronunciations of disordered speech. In *Proceedings of Interspeech’13*, Lyon, France.
- Christensen, H., Casanueva, I., Cunningham, S., Green, P., and Hain, T. (2013b). homeservice: Voice-enabled assistive technology in the home using cloud-based automatic speech recognition. In *4th Workshop on Speech and Language Processing for Assistive Technologies*, pages 29–34.

- Darley, F. L., Aronson, A. E., and Brown, J. R. (1969). Differential diagnostic patterns of dysarthria. *Journal of Speech and Hearing Research*, 12:246–269.
- Darley, F. L., Aronson, A. E., and Brown, J. R. (1975). *Motor speech disorders*. W. B. Saunders and Co., Philadelphia.
- Duffy, J. R. (2005). *Motor speech disorders: substrates, differential diagnosis and management*. Motsby- Yearbook, St Louis, 2nd edition.
- Enderby, P. (1983). Frenchay dysarthric assessment. *Pro-Ed, Texas*.
- Ferrier, L. J., Jarrell, N., Carpenter, T., and Shane, H. C. (1992). A case study of a dysarthric speaker using the dragondictate voice recognition system. *Journal for Computer Users in Speech and Hearing*, 8(1):33–52.
- Fredouille, C. and Pouchoulin, G. (2011). Automatic detection of abnormal zones in pathological speech. In *Intl Congress of Phonetic Sciences (ICPHs'11)*, Hong Kong.
- Galliano, S., Geoffrois, E., Mostefa, D., Choukri, K., Bonastre, J.-F., and Gravier, G. (2005). Ester phase ii evaluation campaign for the rich transcription of french broadcast news. In *Proceedings of Interspeech'05*, pages 1149–1152, September.
- Green, P., Carmichael, J., Hatzus, A., Enderby, P., Hawley, M., and Parker, M. (2003). Automatic speech recognition with sparse training data for dysarthric speakers. In *Proceedings of Interspeech'03*, pages 1189–1192, Geneva, Switzerland.
- Green, J. R., Yunusova, Y., Kuruvilla, M. S., Wang, J., Pattee, G. L., Synhorsti, L., Zinman, L., and Berry, J. D. (2013). Bulbar and speech motor assessment in als: Challenges and future directions. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration*, 14(7–8):494–500.
- Hustad, K. C. (2008). The relationship between listener comprehension and intelligibility scores for speakers with dysarthria. *Journal of Speech, Language and Hearing Research*, 51(3):562–573.
- Joachims, T. (1999). Making large-scale SVM learning practical. In B. Schölkopf, et al., editors, *Advances in Kernel Methods - Support Vector Learning*, chapter 11, pages 169–184. MIT Press, Cambridge, MA.
- Kempler, D. and Van Lancker, D. (2002). Effect of speech task on intelligibility in dysarthria: a case study of parkinson's disease. *Brain and language*, 80(3):449–464.
- Kent, R. D., Weismer, G., Kent, J. F., Vorperian, H. K., and Duffy, J. R. (1999). Acoustic studies of dysarthric speech: Methods, progress, and potential. *The Journal of Communication Disorders*, 32:3:141–186.
- Kim, M. and Kim, H. (2012). Automatic assessment of dysarthric speech intelligibility based on selected phonetic quality features. In *Computers Helping People with Special Needs*, volume 7383 of *Lecture Notes in Computer Science*, pages 447–450.
- Laaridh, I., Fredouille, C., and Meunier, C. (2015a). Automatic detection of phone-based anomalies in dysarthric speech. *ACM Transactions on accessible computing*, 6(3):9:1–9:24, May.
- Laaridh, I., Fredouille, C., and Meunier, C. (2015b). Automatic speech processing for dysarthria: A study of inter-pathology variability. In *Proceedings of Intl Congress of Phonetic Sciences (ICPHs'15)*, Glasgow.
- Lowit, A. and Kent, R. D. (2010). *Assessment of motor speech disorders*, volume 1. Plural publishing.
- McAuliffe, M. J., Ward, E. C., and Murdoch, B. E. (2006). Speech production in parkinson's disease: I. an electropalatographic investigation of tongue-palate contact patterns. *Clinical linguistics & phonetics*, 20(1):1–18.
- Meunier, C., Fougeron, C., Fredouille, C., Bigi, B., Crevier, L., Delais-Roussarie, E., Georgeton, L., Ghio, A., Laaridh, I., Legou, T., Pillot-Loiseau, C., and Pouchoulin, G. (2016). The tyपाल corpus: A collection of various dysarthric speech in read and spontaneous speech. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC'16)*, Portoroz.
- Middag, C., Martens, J.-P., Nuffelen, G. V., and Bodt, M. D. (2009). Automated intelligibility assessment of pathological speech using phonological features. *EURASIP Journal on Applied Signal Processing*, 2009(1).
- Nuffelen, G. V., Middag, C., Bodt, M. D., and Martens, J.-P. (2009). Speech technology-based assessment of phoneme intelligibility in dysarthria. *International journal of language and communication disorders*, 44(5):716–730.
- Parker, M., Cunningham, S., Enderby, P., Hawley, M., and Green, P. (2006). Automatic speech recognition and training for severely dysarthric users of assistive technology: the stardust project. *Clinical Linguistics and Phonetics*, 20(2–3):149–156.
- Rosen, K. M. and Yampolsky, S. (2000). Automatic speech recognition and a review of its functioning with dysarthric speech. *Augmentative and Alternative Communication (AAC)*, 16(1):48–60.
- Rosen, K. M., Kent, R. D., Delaney, A. L., and Duffy, J. R. (2006). Parametric quantitative acoustic analysis of conversation produced by speakers with dysarthria and healthy speakers. *Journal of Speech, Language, Hearing Research*, 49(2):395–411.
- Rudzicz, F., Namasivayam, A. K., and Wolff, T. (2012). The torgo database of acoustic and articulatory speech from speakers with dysarthria. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC'12)*, pages 523–541.
- Scholkopf, B. and Smola, A. J. (2001). *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*. MIT Press, Cambridge, MA, USA.
- Tomik, B. and Guiloff, J. (2010). Dysarthria in amyotrophic lateral sclerosis: a review. *Amyotrophic Lateral Sclerosis*, 11 (1–2):4–15.
- Van Lancker Sidtis, D., Cameron, K., and Sidtis, J. J. (2012). Dramatic effects of speech task on motor and linguistic planning in severely dysfluent parkinsonian speech. *Clinical linguistics & phonetics*, 26(8):695–711.
- Vapnik, V. (1995). *The Nature of Statistical Learning The-*

ory. Springer-Verlag New York, Inc., New York, NY, USA.

Whitfield, J. A. and Goberman, A. M. (2014). Articulatory-acoustic vowel space: Application to clear speech in individuals with parkinson's disease. *Journal of communication disorders*, 51:19–28.

Yorkston, K. M., Strand, E., and Kennedy, M. (1996). Comprehensibility of dysarthric speech: implications for assessment and treatment planning. *American Journal of Speech Language Pathology*, 55:55–66.