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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, distorsion 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.

		Read speech			Spontaneous speech		
Disease	# of speakers	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 $-$

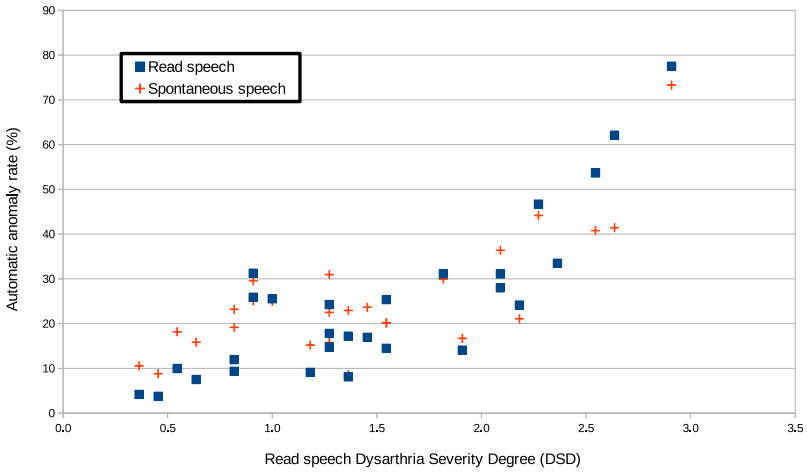


Figure 1: Relationship between the automatic anomaly rate and the dysarthria severity degree when applied on the Typaloc corpus.

anomaly rate over read speech); each point representing one speaker (either control or patient). Observing table 3 and figure 2, we find that, as for control speakers, the automatic approach detects more anomalies on spontaneous speech for PD and CA patients.

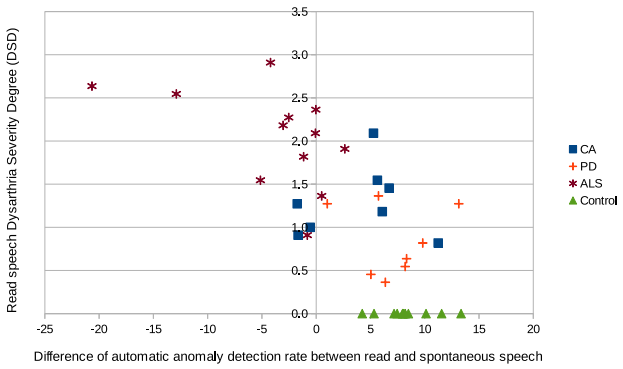


Figure 2: Distribution of differences between spontaneous and read speech anomaly rates according to read speech DSD.

These observations are consistent with results found in (Van Lancker Sidtis et al., 2012; Kempler and Van Lancker, 2002) on patients suffering from PD. In these papers, spontaneous speech was found to be less intelligible and contained more disfluencies than read speech. However, patients suffering from ALS present similar and even lower anomaly rates on spontaneous speech compared to reading (32% and 36% respectively). In our corpus, these patients have the most severe dysarthria (highest DSDs). Further analysis of this behavior is still necessary to study whether this observation is related to intrinsic characteristics of ALS which would affect more the reading task than spontaneous speech production. A second hypothesis is that this behavior is more linked to the severity of the dysarthria of the patients suffering from ALS than the pathology itself. Indeed, the spontaneous speech production task offers to patients more freedom to manage their fatigue, their speech rate and the different phones and sequences of phones or words to produce, which could lead to less anomalies at the phone level.

Finally, table 3 shows a more important increase in automatic anomaly rates computed over spontaneous speech for control speakers compared to dysarthric patients. additionaly, Figure 2 suggests that the difference in anomaly rates between spontaneous and read speech is inversely proportional to the DSD measures. This would suppose that control speakers change more their productions according to the speech style (which results in our case in more anomalies detected over spontaneous speech considering the nature of our models built over read speech) while patients (especially severely dysarthric) loose this capacity to adapt themselves to different styles and tend to make their productions uniform regardless of the task (which results in less differences between measures computed over read and spontaneous speech).

Table 4 reports the automatic anomaly detection rates per pathology, phonetic category and speech style.

For control speakers, all the phonetic categories show higher anomaly rates over spontaneous speech compared to read speech. Fricatives, however, present a more important increase in the anomaly rates from 7% over read speech to 23% over spontaneous speech. For PD patients, fricatives present the highest anomaly rates for both speech styles. Unlike other phonetic categories for which the increase of automatic anomaly rates over spontaneous speech is low, fricatives show an absolute increase of 29% (112% relative). This behavior suggests more an intensification of an already observed phenomenon (high anomaly rate over read speech) linked to the Parkinsonian dysarthria than the emergence of a new one. Observing patients suffering from ALS and even though anomaly rates are more stable across both speech styles, we find still that vowels present less anomalies on spontaneous than read speech (-4% and -18% for oral and nasal vowels respectively). The global decrease

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

	Read speech				Spontaneous speech			
Phonetic category	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.

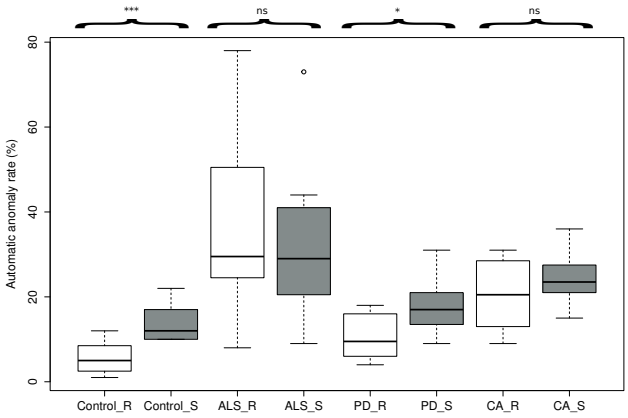


Figure 3: Box plot of automatic anomaly rate per population and speech style.

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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