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# Perceptual Evaluation for Automatic Anomaly Detection in Disordered Speech : focus on ambiguous cases

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## Abstract

Perceptual evaluation is still the most common method in clinical practice for diagnosing and following the condition progression of people suffering from dysarthria (or speech disorders more generally). Such evaluations are frequently described as non-trivial, subjective and highly time-consuming (depending on the evaluation level). Most of the time, perceptual assessment is performed individually by clinicians which can be problematic since judgment may vary from one clinician to the other. Clinicians have therefore expressed the need for new objective evaluation tools better adapted to longitudinal studies, the observation of small units and rehabilitation context to monitor patients' progress. We have previously proposed an automatic approach to the anomaly detection at the phone level for dysarthric speech. The system behavior was studied and validated with different corpora and speech styles and shows good results in this specific task. Nonetheless, the lack of annotated French dysarthric speech corpora has limited our ability to analyze some aspects of its behavior, such as severity, more precisely (more anomalies are detected automatically compared with human experts). To overcome this limitation, we proposed an original perceptual evaluation protocol applied to a limited set of decisions made by the automatic system, relating to the presence of anomalies. Particularly, we intended to focus our analyses on some ambiguous cases in order to enrich our knowledge about the

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system behavior. This evaluation was carried out by a jury of 29 non-naive individuals. Results confirm the relevance of the system for the anomaly detection, and place it within the most severe juries. Besides interesting information related to the system behavior, the evaluation protocol highlighted main differences between human process and the automatic system: humans have difficulties in focusing on small units and they are influenced by contextual information, while the system only focuses on small units. In a way, both approaches are probably complementary.

*Keywords:* Dysarthria, speech disorders, automatic speech processing, perceptual evaluation

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## 1. Introduction

### 2 *Dysarthria: clinical context and limitations*

Dysarthria is a motor speech disorder that is a consequence of neurological damage located either in the central or in the peripheral nervous system. This may result in disturbances in any of the components involved in speech production, such as respiration, phonation, articulation, and prosody. Consequently, this may be reflected by weakness, spasticity, incoordination, involuntary movements, or abnormal muscle tone [1, 2, 3], depending on the location of the neurological damage.

Dysarthric speech has been studied according to different axes and objectives. The pioneer studies, conducted in [4, 1, 5] and pursued in [3], relied on the assumption of an unequivocal association between targeted neurological damage and a set of perceptual alterations in speech production. In these studies, the perceptual evaluation of speech, based on 38 auditory-perceptual features and conducted on a large population of dysarthric speakers, leads to the well-known Mayo clinic classification of dysarthria. This classification is still used in clinical practice for assessment and diagnosis of speaker dysarthria. Indeed, perceptual evaluation by one, or a set of listeners, is still the most common paradigm used to evaluate the characteristics and severity of impairment in speech pathologies.

Other studies focused on measuring the degree of severity of the dysarthria. Such a measurement could be defined according to the patient's intelligibility, comprehensibility, efficiency and perceptual degrees of severity [6]. Orthographic transcription of speech samples (sentences, words, pseudo-words) is

25 also considered a standard method of assessing intelligibility [7] of patholog-  
26 ical speech. Such methods are highly variable considering the different gran-  
27 ularities (phoneme, syllable or word, sentence) and speech production tasks  
28 (read speech, isolated words, pseudo-words or selection of the pronounced  
29 word from a closed list of possible productions, etc.) that could be used.  
30 The clinical evaluation of patients is based on several batteries of tests in  
31 which the production of dysarthric speakers is rated perceptually by clini-  
32 cians. According to the different existing evaluation scales, speech evaluation  
33 can be quantitative or qualitative. Quantitative scales assess whether or not  
34 one of the evaluation criteria is present; answering a yes/no question. Qual-  
35 itative scales, on the other hand, make it possible to rate the severity in an  
36 evaluation item over a given interval.

37  
38 Many examples of perceptual evaluation scales can be presented such as  
39 the Frenchay Dysarthria Assessment (FDA) [8] containing both functional  
40 and perceptual evaluations or the Unified Parkinsons Disease Rating Scale  
41 (UPDRS) in which the 18th item evaluates speech on a 5-point scale.  
42 These batteries evaluate vocal quality, phonetic realizations, prosody, respi-  
43 ration and intelligibility. The BECD (*Batterie d'Evaluation Clinique de la*  
44 *Dysarthrie* in French) [9, 10] is the most commonly-used test by clinicians  
45 for French speech. This test differentiates 35 items in order to characterize  
46 dysarthria, each item is rated on a 5-point scale.

47 Consequently, the use of perception for the evaluation of dysarthric speech  
48 is frequent and well documented. In addition, clinicians who evaluate the  
49 speech of patients are very well trained in detecting the phonetic characteris-  
50 tics associated with the physiopathology of dysarthria. However, a frequent  
51 criticism to perceptual evaluation is the subjectivity of the listeners (both  
52 naive and expert).

53 Several studies [11, 12] report great differences in the perceptual strategies in-  
54 volved in voice-quality evaluation. They point out that, in order to give their  
55 evaluation, listeners ”*compare the stimulus presented to an internal standard*  
56 *or scale*”. Obviously, many parameters may influence the distance between  
57 the stimulus and the listener’s internal standard (regional accent, context,  
58 skills). Moreover, the variability between listeners’ responses may be due  
59 to the signal properties they process primarily (prosody, articulation, etc.).  
60 Indeed, clinicians knowledge of habits with speech disorders and dysarthric  
61 speech production, their knowledge of the condition of the dysarthric speakers  
62 and their degree of exposure to the speakers speech alterations may influence

63 the evaluation results. This subjectivity associated with perceptive evalua-  
64 tion reduces its relevance and makes it inadequate in longitudinal studies  
65 for example. Nonetheless, evaluation by clinicians, even if subjective, is not  
66 incoherent. Most of the time, this subjectivity reflects a granularity in the  
67 perception of the degree of deviance.

68 An additional difficulty for speech perceptual evaluation is due to the nature  
69 of speech itself. Indeed, the production of healthy speakers is character-  
70 ized by massive phonetic variations [13]. When the syntactic and semantic  
71 contexts are limited, which is often the case in perceptual experiments, varia-  
72 tion may be difficult to interpret and may increase the ambiguity of listeners'  
73 judgment. Consequently, listeners may have difficulty in concentrating their  
74 judgment on short linguistic units due to a lack of contextual information.  
75 These limitations in speech evaluation and in human perception are difficult  
76 to fix. Nevertheless, the variation in listeners' judgment does not system-  
77 atically suggest random responses and consistent results are often provided  
78 despite listeners' variable responses. In fact, the impact of variability in jurors'  
79 responses is minimized when protocols involve a large number of subjects.

#### 80 *Dysarthria: towards automatic approaches*

81 To cope with these limitations, automatic approaches have rapidly emerged,  
82 as potential solutions, by providing objective tools for intelligibility assess-  
83 ment and anomaly detection in pathological speech [14]. In the literature, we  
84 distinguish two main approaches: those directly based on automatic speech  
85 transcription and word transcription error rate to compute an intelligibility  
86 score [15, 16], and those using automatic speech processing techniques as a  
87 means of extracting relevant information from the speech signal to perform an  
88 automatic evaluation of speech on different granularities [17, 18, 19, 20, 21].  
89 In previous work, the authors proposed an automatic approach for phone-  
90 based anomaly detection [22] in dysarthric speech. By detecting and locating  
91 anomalies in speech production, this approach aimed to enhance manual in-  
92 vestigation by human experts and, at the same time, to reduce the extent of  
93 their intervention by scrutinizing the speech signal. Indeed, this automatic  
94 process should make it possible to cover a significant quantity of speech pro-  
95 duction while guiding human experts towards the examination of specific  
96 parts of the speech, considered atypical. This process is notably interest-  
97 ing for speech production of people with mild to moderate dysarthria, for  
98 whom speech impairment may be scattered along the speech signal. More-  
99 over, this automatic detection and location of abnormal acoustic phenomena

100 can have applications in clinical practice. For example, the evaluation of  
101 dysarthria by clinicians could be partially helped by a visual display of ab-  
102 normal phenomena located in the speech production of dysarthric speakers,  
103 like a map. In the same manner, maps could be relevant in comparing the  
104 speech productions of a dysarthric speaker over time, during clinical treat-  
105 ment or rehabilitation for instance. Finally, this automatic process could be  
106 extended to other kinds of speech disorder resulting in acoustic alterations  
107 in the speech signal, such as neck or head cancers.

### 108 *Motivations*

109 In this paper, the authors investigate the behavior of the system, and in  
110 particular its potential or shortcomings, mainly over-detection of anomalies  
111 compared to a human expert. More significantly, this work attempts to tackle  
112 the question of the relationship between the human perception of alterations  
113 in speech and their modeling by automatic speech processing systems. In  
114 this context, the objective of this work is to propose an original perceptual  
115 evaluation protocol, suitable for evaluating the performance of the automatic  
116 system. This evaluation protocol aims at comparing the decisions relating to  
117 the presence of anomalies yielded by the automatic system to those of a jury  
118 composed of a large set of expert listeners (in order to minimize the effect  
119 of individual subjectivity). Both automatic and human decisions are made  
120 with regard to a selection of speech sequences produced by a large number  
121 of dysarthric patients representing four different pathologies, and by control  
122 speakers.

123

124 The rest of this article is organized as follows: section 2, the context of  
125 this research work is presented. The experimental protocol and methodology  
126 for the perceptual evaluation is presented in section 3. In section 4, the  
127 evaluation results are presented according to different aspects, while section 5  
128 raises the question of automatic system performance and the jury's judgment  
129 tendencies. Finally, section 6 provides a conclusion and directions for future  
130 work.

131 **2. Context: Automatic Anomaly Detection Approach and Dysarthric**  
132 **Corpora**

133 *2.1. Automatic Anomaly Detection Approach*

134 The automatic phone-based anomaly detection system relies on two steps  
135 : a text-constrained phone alignment to obtain the phone segmentation and  
136 a classification of speech segments into normal and abnormal phones (anoma-  
137 lies).

138 The automatic phone segmentation of the speech utterances into phones  
139 is carried out with the help of an automatic text-constrained phone alignment  
140 tool. This tool takes into account the parameterization of the speech signals  
141 produced by a given speaker, gender-dependent acoustic models of French  
142 phones, the sequence of words pronounced by the speaker in each utterance  
143 and a phonetized, phonologically-varied lexicon of words based on a set of 37  
144 French phones. The sequence of words comes from a manual orthographic  
145 transcription performed by a human listener following some annotation rules.

146 The automatic alignment process is then based on a Viterbi decoding  
147 and graph-search algorithms, the core of which is the acoustic modeling of  
148 each phone, based on a Hidden Markov Model (HMM). In this work, each  
149 phone is modeled using a 3-state context-independent HMM topology which  
150 are built using the Maximum Likelihood Estimate paradigm on the basis of  
151 about 200 hours of French radiophonic speech recordings [23]. In order to get  
152 speaker-dependent models, a three-iteration Maximum A Posteriori (MAP)  
153 adaptation is performed to adapt all the HMM parameters.

154 This automatic alignment process results in a couple of start and end  
155 boundaries per phone produced in the speech recordings. The precision of  
156 this automatic phone alignment was studied according to dysarthric and  
157 phonetic classes in [24].

158 On the basis of this alignment, a set of features considered as relevant  
159 for the anomaly detection task are extracted over each segment  $y_p$  associated  
160 with the phone  $p$ . The list of the used features can be found in [22]. These  
161 phone features are then fed into a 2-class automatic classification system  
162 based on Support Vector Machines (SVM). The SVM classification method  
163 has been largely applied in pattern recognition problems [25, 26]. Here the  
164 method is used in a 2-class classification task: the discrimination between  
165 normal and abnormal (anomaly) phones. Figure 1 describes the automatic  
166 anomaly detection process.

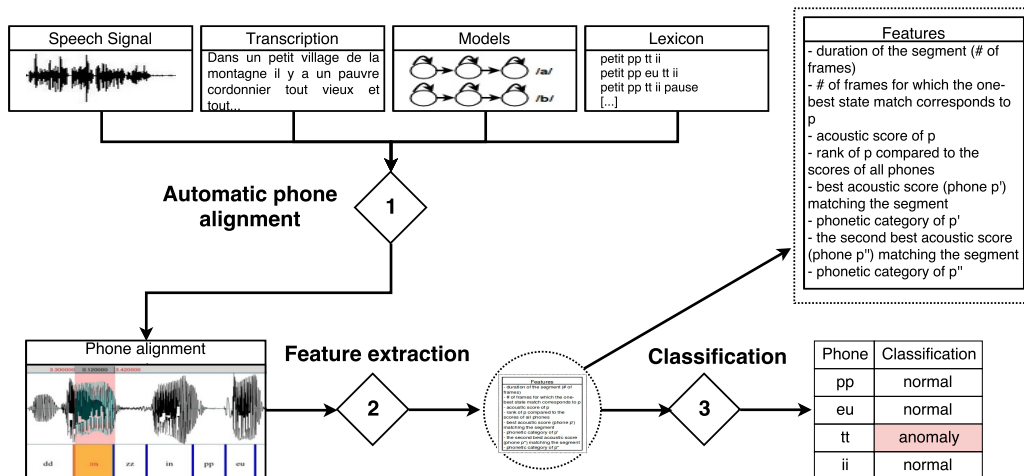


Figure 1: Automatic approach for phone-level anomaly detection.

167 In [22], the system was evaluated on a very limited corpus of dysarthric  
 168 speech (4 female and 4 male dysarthric patients, suffering from the same  
 169 pathology and 6 control speakers) annotated by one human expert. This  
 170 annotation was made specially for system development and evaluation, by  
 171 labeling each phone as deviant or not from an acoustic point of view. On  
 172 this corpus, the system obtained a quite high averaged recall measure <sup>1</sup> of  
 173 0.81 (0.72 in male patients and 0.89 in female patients) and a less convincing  
 174 averaged precision measure<sup>2</sup> of 0.63 (0.61 in male patients and 0.65 in female  
 175 patients). Still in this work, the automatic system was applied on a non anno-  
 176 tated corpus, implying a larger number of speakers (118 dysarthric patients  
 177 and control speakers) and different pathologies like Parkinson’s Disease (PD),  
 178 Amyotrophic Lateral Sclerosis (ALS), and Cerebellar Ataxia (CA). Since no  
 179 labeled data regarding anomalies was available, evaluation was carried out  
 180 by observing the relationship between the rate of speech anomalies reported  
 181 by the automatic system and the perceptual rates given by an expert jury on  
 182 the global severity degree of dysarthria, the global degree of intelligibility and

<sup>1</sup>The ratio between the number of phones correctly detected as anomalies by the automatic approach and the number of zones labeled as abnormal in the reference.

<sup>2</sup>The ratio between the number of phones correctly detected as anomalies by the automatic approach and the total number of anomalies reported by the automatic processing (truly or falsely).



183 of articulation impairment, and finally, the speech rate of speakers. Analysis  
184 of the results pointed out some very interesting behavior of the automatic  
185 system, which exhibits quite relevant correlations with the majority of the  
186 perceptual criteria (e.g. between 0.8 and 0.9 for almost all of the patholo-  
187 gies for the global severity degree). In another work [27], the application of  
188 the automatic anomaly detection on read and spontaneous speech still high-  
189 lighted the interest of such an approach.

190

## 191 2.2. Dysarthric speech corpora

192 All the selected speech sequences used in this work were extracted from  
193 French read speech recordings of the fairy tale "Tic Tac" (The elves and  
194 the shoemaker). In total, 40 speakers (21 male and 19 female speakers)  
195 from dysarthric speech corpora *VML* and *TypALoc* [28] were selected. Four  
196 pathologies were represented in these corpora:

- 197 • Cerebellar Ataxia (CA), caused by lesions of the cerebellum or its path-  
198 ways. The cerebellum controls the balance and coordination of move-  
199 ments, which gives it a major role in voluntary motor control [29]. CA  
200 results in alterations in spatial-temporal organization of movement and  
201 is associated with ataxic dysarthria in the Darley classification;
- 202 • Parkinson's Disease (PD), is one of the most common degenerative neu-  
203 rological diseases in the world. It is linked to dysfunctions in the central  
204 nervous system, resulting from the death of cells in the substantia ni-  
205 gra region in the brain and, the lack of dopamine in these areas. This  
206 causes a chronic dysfunction of the central gray nuclei, essential for  
207 the execution and the control of learned motor plans [30]. The causes  
208 of this disease are still unknown and likely to include environmental,  
209 genetic, and lifestyle factors [31]. PD is associated with hypokinetic  
210 dysarthria in the Darley classification;
- 211 • Amyotrophic Lateral Sclerosis (ALS), is a primary degenerative neuro-  
212 logical disease affecting both upper and lower motor neurons. It causes  
213 the progressive loss of motor power and has no curative treatment.  
214 Other symptoms include muscle weakness, atrophy, loss of control of  
215 all voluntary movements, postural instability and speech, phonation  
216 and swallowing difficulties. ALS is associated with a mixed dysarthria  
217 in the Darley classification;

218 • Lysosomal diseases (LYS) include several disorders that affect the lyso-  
 219 somes (entities present in each of our cells that interfere in recycling  
 220 materials resulting from cellular functioning). Lysosomes fulfill their  
 221 function thanks to three types of enzymes they contain and the alter-  
 222 ation, due to genetic reasons, of this functioning results in a lysosomal  
 223 disease. These diseases are often associated with mixed dysarthria.  
 224 Two lysosomal disorders are represented in our corpora: Tay-Sachs  
 225 and Niemann-Pick C diseases.

226 All the speech recordings of patients were evaluated perceptually by a  
 227 jury of 11 experts who were asked to rate each patient on perceptual items of  
 228 speech quality according to the GEPD evaluation protocol (a perceptive eval-  
 229 uation protocol containing 9 items based on the BECD evaluation protocol  
 230 [9]). These items included the Dysarthria Severity Degree (DSD) rated on a  
 231 scale of 0 to 3 (0 -no dysarthria, 1 -mild, 2 -moderate, 3 -severe dysarthria)  
 232 and other items such as intelligibility, articulation impairment and speech  
 233 rate. Three dysarthria severity degree groups were established according to  
 234 the averaged perceptual evaluation issued by the jury: (1) patients with a  
 235 DSD  $\leq 1.5$  are in severity group 1 (2) patients with DSD  $\leq 2.5$  are in severity  
 236 group 2 (3) patients with DSD  $> 2.5$  are in severity group 3.

237  
 238 Table 1 details the number of patients and sequences for each pathology  
 and their dysarthric class.

Population	Corpora	Dysarthria class	# of speakers	# of sequences
Control speakers	<i>TypALoc</i>	-	7	15
Parkinson’s disease	<i>TypALoc</i>	Hypokinetic	6	15
Cerebellar ataxia	<i>TypALoc</i>	Ataxic	8	22
Amyotrophic Lateral Sclerosis	<i>TypALoc</i>	Mixed	11	28
Lysosomal storage disease	<i>VML</i>	Mixed	8	18
Total	-	-	40	98

Table 1: Information related to the corpora used for the perceptual evaluation task including the different populations and dysarthria class - control speakers and patients suffering from Parkinson’s disease, cerebellar ataxia, amyotrophic lateral sclerosis, and lysosomal diseases, the number of speakers and of speech sequences per population.

### 240 3. Perceptual evaluation protocol and methodology

241 As mentioned above, the aim of this work was to cope with the lack  
242 of annotated corpora appropriate for evaluating the automatic detection of  
243 anomalies in speech produced by patients suffering from speech disorders,  
244 compared with normal speech. Generally, the annotation of corpora is costly  
245 and time-consuming. In our context, difficulties are increased by the fact  
246 that the automatic detection of anomalies is carried out at the phone level.  
247 A previous unpublished work we did demonstrated that the perceptual eval-  
248 uation of the presence of anomalies in speech production by humans at the  
249 phone level is a very complex task, leading to very heterogeneous decisions,  
250 even when involving a large number of listeners. Based on these observa-  
251 tions, we have proposed an original perceptual evaluation protocol of the  
252 outputs of the automatic system on the word level. The task of the jury of  
253 listeners in this protocol is still to determine the presence or not of speech de-  
254 viance (anomalies), in terms of articulatory realization on sequences already  
255 annotated automatically by the approach.

#### 256 3.1. Protocol design

257 The first feature of this protocol was to transpose the decision of the  
258 automatic system, initially at the phone level, to the word level, to facilitate  
259 the perceptual evaluation done by humans. In this way, each monosyllabic  
260 word including, at least, one phone detected as an anomaly by the automatic  
261 system was considered as abnormal. In parallel, the presence of two phones,  
262 at least, detected as anomalies in a polysyllabic word makes it abnormal.  
263 Figure 2 depicts an example of a cartography representing the automatic  
264 annotation of the production of a patient at the word level; white boxes  
265 match normal words, red boxes match abnormal words and yellow boxes  
266 represent polysyllabic words containing only one abnormal phone.

267 The second feature of this protocol was the set of speech sequences used  
268 for the perceptual evaluation task. Due to the cost of such tasks mentioned  
269 above, the totality of corpora automatically annotated by the system could  
270 not be used. The concentration level and cognitive effort required for each  
271 participant for the evaluation task had also to be taken into account. For  
272 these different reasons, this set of speech sequences had to be limited in size,  
273 in order to make the task feasible and efficient while relevant for the assess-  
274 ment of the quality of the automatic system decisions. In this way, the entire

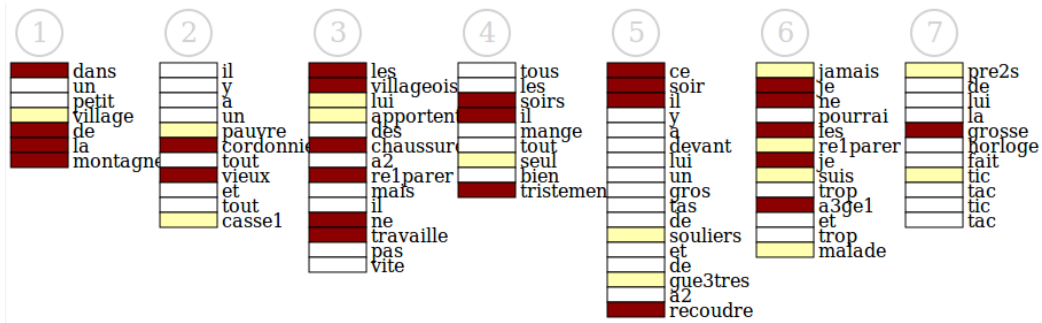


Figure 2: An example of the word-level automatically detected anomaly cartography. White boxes match normal words, red boxes match abnormal words and yellow boxes represent polysyllabic words containing only one abnormal phone.

275 speech corpus described in the previous section was listened to by two final-  
 276 year speech therapy students <sup>3</sup>. Firstly, their listening made it possible to  
 277 exclude recordings with low signal quality, noise or other disturbing elements.  
 278 Secondly, coupled with the automatic annotation of anomalies provided by  
 279 the system (figure 2), this listening highlighted different cases judged to be  
 280 relevant for a finer analysis of the system behavior. Among these cases, typi-  
 281 cal errors of automatic detection systems were identified as false positives  
 282 (also called false alarms), which meant that the automatic system had de-  
 283 tected a phoneme as an anomaly whereas it was not, or false negatives, which  
 284 meant that the automatic system had not detected an anomaly which was  
 285 present. Contrarily, the correct detection decisions taken by the automatic  
 286 system were identified as a third relevant case. Finally, in some ambiguous  
 287 cases, it was possible to question and reconsider those automatically-detected  
 288 anomalies, according to the listeners. Taking these considerations into ac-  
 289 count, the two speech therapists selected a limited set of sequences from the  
 290 entire speech corpus and pre-classified them according to four categories for  
 291 validation by the jury of experts as reported in the next section.

292 *3.2. Speech material for perceptual evaluation*

293 The selected sequences were extracted from the recordings using Praat  
 294 [32]. Artificial silences of 400ms and 200ms were added to each at the be-  
 295 ginning and the end respectively in order to avoid abrupt signal cuts for the

---

<sup>3</sup>These two speech therapists participated in the design of the perceptual evaluation protocol, but did not take part in the evaluation jury described later.

296 perceptual evaluation process.

297 A speech sequence contained one or several words targeted for the percep-  
298 tual evaluation. For example, in the sequence "il *mange* tout seul bien  
299 *tristement*" (*he eats very sadly alone*), the words "*mange*" (*eats*) and  
300 "*tristement*" (*sadly*) are targeted for the evaluation; the other words of  
301 the sequence were considered to be normally produced by the system and  
302 both speech therapists (referred to as annotators in the rest of the paper).

303

304 The different speech sequences were chosen to fit one of the following four  
305 predefined categories, regarding uniquely the target word(s) (as mentioned  
306 above, the rest of the words occurring in the speech sequences were considered  
307 as normal by the annotators and the system, independently of the categories)

308 :

- 309 • 12.5% were referred to as "obvious segments". Here, both annotators  
310 agreed with the system annotation considering the target word(s) as  
311 abnormal; This category is rather limited in size, compared to the  
312 others since the authors were more interested by the potentially wrong  
313 behavior of the automatic system;
- 314 • 37.5% were referred to as "ambiguous segments". Here, the human  
315 annotators disagreed and were not able to decide whether the automatic  
316 annotation, considering the target word(s) as abnormal, was correct or  
317 not;
- 318 • 25% were referred to as "false negatives". Here, both annotators con-  
319 sidered that the system failed to detect the presence of a true anomaly  
320 on the target word(s);
- 321 • 25% were referred to as "false positives". Here, both annotators con-  
322 sidered that the system falsely labeled the target word(s) as abnormal.

323 Other factors shaped the set of the speech sequences. First of all, efforts  
324 had been concentrated on selecting speech produced by the largest number  
325 of patients, and representing the four pathologies available in our corpora.  
326 Secondly, efforts were made to balance the selected sequences and targeted  
327 words in order to vary their nature (grammatical, and lexical words), their  
328 length (long and short words) and their position in the sequence (start, mid-  
329 dle, and end).

330 To respond to these different constraints, a total of 98 speech sequences pro-  
331 duced by 40 speakers, including 33 dysarthric patients and 7 healthy control  
332 speakers, were finally selected for the perceptual evaluation task.

333

334 The last feature of the protocol relies on the choices of the listeners and  
335 their degree of expertise in evaluating whether or not abnormal words were  
336 present in the speech sequences. The aim of this perceptual evaluation proto-  
337 col is to evaluate the quality of the outputs of an automatic system, consid-  
338 ered itself as an "expert" since its goal is to bring some objective "expertise"  
339 to clinicians or phoneticians in their analysis of speech disorders. It seemed  
340 natural to demand that listeners, qualified in evaluating such speech disor-  
341 ders, participate in this evaluation protocol. A jury of expert listeners was  
342 therefore selected.

### 343 *3.3. Participants*

344 The selected jury included 29 experts aged between 22 and 58 (average  
345 age of 33). They all had French as their mother tongue and had no prior  
346 audition or learning disorders. The jury was composed of:

- 347 • 1 Ear, Nose and Throat (ENT) specialist, and speech pathologist;
- 348 • 10 speech therapists;
- 349 • 18 final-year speech therapy students.

### 350 *3.4. Instructions and experimental implementation*

351 The proposed perceptual evaluation task was then computerized using  
352 Perceval [33], an automated platform for perceptual auditory and visual tests,  
353 which can run on any Windows equipped computer. Evaluations were per-  
354 formed in quiet rooms and lasted between 25 and 40 minutes depending on  
355 participants. Also, each evaluation took place in one session only with no  
356 pause allowed and all participants used the same headphone set during the  
357 experiment.

358 The experiment was performed as follows:

- 359 1. participants were presented with an instruction list to read on the  
360 screen (see Appendix A for the translated text of the instruction list  
361 given to the listener);

- 362 2. an oral instruction was then given to all participants indicating that  
363 they should focus solely on articulatory realization and not to take  
364 prosodic or vocal aspects into account;
- 365 3. a training phase of 4 sequences was proposed in order to get the par-  
366 ticipant familiarized with the task and the use of Perceval platform;
- 367 4. the evaluation started. An orthographic transcription of the sequence  
368 appeared on the screen. Under each word, the expert had to check one  
369 of two boxes to label the word as "**normal**" or "**abnormal**". Figure  
370 3 shows an example screen shot of the experiment. The expert could  
371 listen to each sequence up to 3 times but then had to give his/her  
372 evaluation.

373 It is worth noting that no information about the category the speech  
374 sequence belonged to was communicated to the experts during the perceptual  
375 evaluation. Speech sequences were presented for each listener in a totally  
376 randomized order, independently of categories.

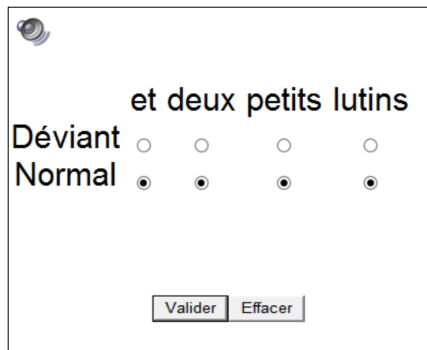


Figure 3: Screen shot from the Perceval platform used for the perceptual evaluation. The sequence tested is "et deux petits lutins" (*and two little elves*). The expert had to check one of two boxes to label each word as "**normal**" or "**déviant**" (*abnormal*) and press the "valider" (*confirm*) button.

### 377 3.5. System-Jury agreement measures

378 To compare the decisions made by the expert jury during their perceptual  
379 evaluation on the set of speech sequences and those of the automatic system,  
380 several agreement rates were computed:

- 381 • The *AG\_targetAnomaly* rate, measuring the System-Jury agreement  
382 rate on the target words of each sequence automatically labeled as  
383 abnormal for the "obvious segments", "ambiguous segments" and "false  
384 positives" categories. This rate measures the capacity of the automatic  
385 processing in detecting present abnormal zones and how much the jury  
386 agrees with it on the detected segments. The closer to 100 the rate is,  
387 the better the automatic system detects the abnormal zones;
- 388 • the *AG\_targetNormal* rate, measuring the System-Jury agreement rate  
389 on the target words of each sequence automatically labeled as normal  
390 for the "false negatives" category. This rate reflects the system inability  
391 to detect potential present anomalies (according to the two annotators).  
392 The closer to 100 the rate is, the better the automatic approach is in  
393 distinguishing anomalies from normal words and not labeling them as  
394 abnormal;
- 395 • the *AG\_nonTargetNormal* rate, measuring the System-Jury agree-  
396 ment rate on the non-target words labeled automatically as normal  
397 for the different test sequence categories. This rate measures the sys-  
398 tem precision and capacity to distinguish between normal and abnormal  
399 words. The closer to 100 the rate is, the better the automatic approach  
400 is in not labeling normal words as anomalies;

## 401 4. Results

402 In this section, we present and discuss the evaluation results according  
403 to the predefined categories of the speech sequences (subsection 4.1), to the  
404 different pathologies (subsection 4.2), and to the severity degrees (subsection  
405 4.3) present in our corpora. The results will be presented, in each case,  
406 by computing and analyzing the agreement rates presented earlier. Also,  
407 an additional analysis of the evaluation results focusing on a sub-jury of 7  
408 selected experts is provided in subsection 4.4.

### 409 4.1. Results according to test sequence categories

#### 410 4.1.1. Target abnormal words detected by the automatic approach

411 Figure 4 depicts the distribution of *AG\_targetAnomaly* when computed  
412 for the test categories "obvious segments", "ambiguous segments" and "false  
413 positives" and *AG\_targetNormal* when computed on test category "false



414 negatives”.



Figure 4: System-Jury *AG\_targetAnomaly* and *AG\_targetNormal* agreement rates (%) on automatically detected abnormal words (“obvious segments”, “ambiguous segments” and “false positives”) and words labeled as normal (“false negatives”).

415

416 We observe a high degree of heterogeneity in the results depending on  
417 the test category reaching 78%, 58% and 13% for “obvious segments”, “am-  
418 biguous segments” and “false positives” categories respectively (target words  
419 labeled as anomalies by the system).

420 The high *AG\_targetAnomaly* rate on “obvious segments” confirms the  
421 ability of the automatic approach to detect highly distorted segments. This  
422 ability was also highlighted in [22] where the approach was able to detect  
423 81% of phone-based anomalies annotated by an expert.

424 In contrast, the low *AG\_targetAnomaly* rate of 13% observed on “false pos-  
425 itives” reveals the limits of the proposed approach and its somehow approx-  
426 imate judgment when facing more subtle anomalies. This result calls for a  
427 more in-depth acoustical analysis of these segments in order to better com-  
428 prehend the automatic system behavior and whether these segments could  
429 be related to acoustic distortions (noise, breaths, etc.) of non-pathological  
430 nature. Nevertheless, other hypotheses could also be advanced to explain  
431 this behavior such as the presence of true anomalies, which are not detected  
432 by human experts in these segments, or the presence of erroneous data in the

433 perceptual annotation made by an expert and used as reference to train the  
434 automatic anomaly detection system.

435

436 Considering the "ambiguous segments" test category, the System-Jury  
437 *AG\_targetAnomaly* rate confirms the difficulty and the non trivial nature  
438 of the perceptual evaluation of dysarthric speech task even when performed  
439 by experts. Here, almost half (58%) of the jury decisions agreed with the  
440 system on the presence of an anomaly on the target words.

#### 441 4.1.2. Target abnormal words undetected by the automatic approach

442 In this section, the focus is made on "assumed" anomalies raised by both  
443 our annotators, that the automatic system did not detect, still by observing  
444 the System-Jury agreement rate. So, considering the "false negatives" cat-  
445 egory depicted in figure 4, the System-Jury *AG\_targetNormal* rate reaches  
446 30%. This pretty significant rate shows that the expert jury seems neither to  
447 fully approve nor disapprove of the system behavior and the non detection of  
448 anomalies in the targeted word. Almost 1 expert in 3 agreed with the system  
449 decision.

450 It is worth noting that some of these test sequences contained anomalies  
451 related to word substitutions made by some speakers while reading. These  
452 substitutions were included in the manual orthographic transcription used for  
453 the text-constrained phone alignment and, therefore were taken into account  
454 by the automatic approach. However, these substitutions were not included  
455 in the perceptual evaluation process and were consequently detected by the  
456 jury of experts as anomalies. When such words are not considered in the  
457 result analysis, the *AG\_targetNormal* reaches 36.3%.

#### 458 4.1.3. Non-target normal words

459 Figure 5 depicts the distribution of *AG\_nonTargetNormal* when com-  
460 puted on each test category.

461 We note that high System-Jury agreement rates on normal words are ob-  
462 served reaching 83%, 89%, 85% and 95% on "obvious segments", "ambiguous  
463 segments", "false negatives" and "false positives" respectively.

464 These rates allowed us to balance the low *AG\_targetAnomaly* rate ob-  
465 served earlier in the "false positives" category. Indeed, the System-Jury  
466 overall agreement rate, *AG\_nonTargetNormal*, on automatically annotated  
467 non target normal words, across all test categories, reaches 88%. This result  
468 confirms that the automatic approach behavior is far from being arbitrary

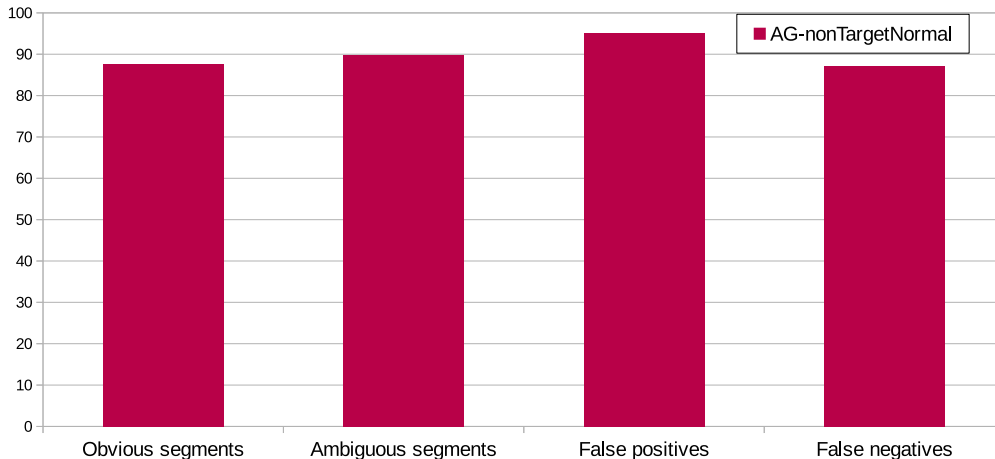


Figure 5: System-Jury *AG\_nonTargetNormal* agreement rates (%) on non target normal words per test sequence category.

469 and the observation made on the "false positives" category could be consid-  
 470 ered as marginal and restrained to a small amount of speech segments. It  
 471 would be more appropriate to describe the system behavior as more severe  
 472 compared to the human experts.

473

#### 474 4.2. Inter-population variability

##### 475 4.2.1. Target abnormal words detected by the automatic approach

476 Table 2 details the System-Jury *AG\_targetAnomaly* rates per population  
 477 and test category.

478 We note that the best *AG\_targetAnomaly* rate occurred in patients suffer-  
 479 ing from lysosomal diseases (LYS) reaching 98.3% and 68.1% on "obvious  
 480 segments" and "ambiguous segments" respectively. This tendency was to be  
 481 expected considering that this population was involved in the modeling of  
 482 the abnormal phones in the automatic system and is consistent with previ-  
 483 ous results in [22]. This does also highlight the importance of the training  
 484 phase in such an automatic approach and suggests that the use of more data  
 485 associated with different pathologies and dysarthric classes would improve  
 486 the system performance, which is already very promising given the results  
 487 reported earlier.

488

	Obvious segments	Ambiguous segments	False positives
CTRL	81.0	15.2	1.4
CA	71.3	59.8	9.8
PD	78.2	42.7	8.6
ALS	74.6	79.0	19.6
LYS	98.3	68.1	15.5

Table 2: System-Jury *AG\_targetAnomaly* agreement rates (%) on automatically detected target abnormal words per population and test sequence category

489 Considering the other populations, we found that the jury members, de-  
490 spite their expertise level in pathological speech evaluation, were influenced  
491 by the acoustic characteristic and the overall speech quality of speakers. This  
492 is highly important considering that the instructions given to the jury explic-  
493 itly restricted the evaluation task to the articulatory production of speakers.  
494 This jury’s behavior is particularly observed on patients suffering from ALS  
495 for whom the jury members annotated the most anomalies compared to other  
496 populations and the *AG\_targetAnomaly* rate reaches 19.6% on the ”false pos-  
497 itives” category. Indeed, the mixed dysarthria associated with this pathology  
498 is characterized by a general hypernasality, hoarseness and low speech rate.  
499 This resulted in the tendency of the jury to annotate more anomalies than  
500 expected on this population. In contrast, an opposite behavior was observed  
501 on control speakers and patients suffering from Parkinson’s disease for whom  
502 the overall good quality of the speech discouraged the jury members from  
503 annotating segments as anomalies and the computed *AG\_targetAnomaly*  
504 rate over the ”ambiguous segments” reaches 15.2% (CTRL) and 42.7% (PD)  
505 respectively.

#### 506 4.2.2. Target abnormal words undetected by the automatic approach

507 Table 3 details the System-Jury *AG\_targetNormal* rates per population  
508 for the ”false negatives” test category.  
509 Here, it is interesting to notice that for control speakers, the jury agreed half  
510 of the time with the automatic approach whereas, for patients suffering from  
511 severe dysarthria such as ALS, CA and LYS, they tended to annotate more  
512 anomalies than the system did. This behavior suggests, once more, that the  
513 jury was highly influenced by the contextual information and the specific  
514 traits of each pathology.

	False negatives
CTRL	50.6
CA	24.9
PD	64.4
ALS	25.6
LYS	8.6

Table 3: System-Jury *AG\_targetNormal* agreement rates (%) on automatically undetected abnormal words ("false negatives") per population

516 Also, we note that patients suffering from PD present quite singular be-  
 517 havior since the jury agreed with the system on the absence of an anomaly on  
 518 the target words with a rate of 64.4%. This rate is even higher than the one  
 519 observed in the control speakers (50.6%). This observation is somewhat sin-  
 520 gular and will require a more in-depth analysis of the set of speakers selected  
 521 in both populations to explain this behavior.

#### 522 4.2.3. Non-target normal words

523 Table 4 details the System-Jury *AG\_nonTargetNormal* rates per popula-  
 524 tion and test categories ("obvious segments", "ambiguous segments", "false  
 525 negatives" and "false positives" test categories).

526

	Obvious segments	Ambiguous segments	False negatives	False positives
CTRL	99.1	99.7	97.5	100.0
CA	92.3	86.4	86.6	94.6
PD	89.1	93.7	91.2	97.3
ALS	52.9	77.1	75.3	98.0
LYS	81.9	86.6	72.9	85.6

Table 4: System-Jury *AG\_nonTargetNormal* agreement rates (%) on non target normal words per population and test sequence category

527 We observe that for almost all populations and test sequences, the System-  
 528 Jury *AG\_nonTargetNormal* rates is higher than 70% reaching 100% on  
 529 "false positives" sequence produced by the control speakers. In contrast,

530 we note that this rate is only 52.9% in non target normal words from the  
531 "obvious segments" sequences produced by ALS patients. This low result  
532 still emphasizes the importance of the contextual information for the expert  
533 jury during perceptual evaluation. Indeed, the *AG\_nonTargetNormal* rate  
534 in ALS patients reaches 77.1% in non target normal words when surrounded  
535 by ambiguous and not prominent anomalies ("ambiguous segments") com-  
536 paring to the 52.9% rate observed in non target normal words produced in  
537 an obviously deviant context ("obvious segments").

### 538 4.3. Severity variability

#### 539 4.3.1. Target abnormal words detected by the automatic approach

540 Table 5 details the System-Jury *AG\_targetAnomaly* rates per dysarthria  
541 severity degree group and test sequence category.

542  
543 Considering the "obvious segments" and "ambiguous segments" cate-  
544 gories, we observe that the highest computed agreement rates are observed  
545 in patients in the severity group 2 (moderate dysarthria) reaching 95.7% and  
546 83.9% over both test categories respectively. This behavior was expected  
547 for the "obvious anomalies" test sequence category since the severity group  
548 2 contains the most dysarthric patients used in this category (no segment  
549 produced by patients suffering from severe dysarthria were used). However,  
550 it is interesting that the agreement rate for the "ambiguous segments" for  
551 severity 3 group reaches only 51.7%.

552 One hypothesis to explain this behavior could be related to the dysarthria  
553 effect on all speech components. Indeed, the segments produced by patients  
554 from severity group 3 used in the "ambiguous segments" category are pro-  
555 duced by one single patient, suffering from LYS and having an extremely low  
556 speech rate as well as articulation impairments. The automatic system could  
557 be disturbed by such speech productions, considering notably that the acous-  
558 tic models used in the alignment process are based on radiophonic recordings  
559 (section 2.1), resulting in many more anomalies detected automatically. In  
560 contrast, the jury was asked to consider only articulation related anomalies  
561 and to ignore prosodic (or other) aspects. This behavior suggests that even  
562 though the design of the automatic approach did not target prosody related  
563 anomalies, such an impairment could influence it.

564 Considering the "false positives" test category, we observe that the *AG\_targetAnomaly*  
565 rate reaches 31.7% for moderate dysarthria (severity group 2), but extremely  
566 low rates for the other groups of severity degree (8.0% and 1.4% for severity

567 group 1 and the control speaker respectively). This tendency shows that  
 568 the expert jury could be highly influenced by the severity of the dysarthria  
 569 and tended to 'systematically' annotate anomalies for moderate and severe  
 570 dysarthria even in normal sequences and words.

	Obvious segments	Ambiguous segments	False positives
CTRL	81.0	15.2	1.4
Severity 1	71.6	47.0	8.0
Severity 2	95.7	83.9	31.7
Severity 3	-	51.7	-

Table 5: System-Jury *AG\_targetAnomaly* agreement rates (%) on automatically detected target abnormal words per dysarthria severity degree and test sequence category.

#### 571 4.3.2. Non-target normal words

572 Table 6 details the System-Jury *AG\_nonTargetAnomaly* rates per dysarthria  
 573 severity degree group and test category.

574 Considering all test categories, we note that higher System-Jury agreement  
 575 rates are computed over control speaker and mild dysarthric patients. In  
 576 fact, the higher the dysarthria is, the lower the agreement rate on normal  
 577 words is (jury members annotate more anomalies). Once again, this behavior  
 578 proves the subjective character of perceptual evaluation and the fact that the  
 579 jury members were impacted by both the pathology and the severity of the  
 580 dysarthria when evaluating each segment.

	Obvious segments	Ambiguous segments	False negatives	False positives
CTRL	99.1	99.7	97.5	100.0
Severity 1	91.4	92.2	86.7	95.9
Severity 2	49.1	78.2	71.8	80.2
Severity 3	-	48.3	-	-

Table 6: System-Jury *AG\_nonTargetNormal* agreement rates (%) on non target normal words per dysarthria severity degree and test sequence category.

581 4.4. Additional analysis on a sub-jury

582 A more detailed analysis of listeners responses showed that the overall  
 583 perception of anomalies increases from 8% to 33% depending on the listener  
 584 (Figure 6). This suggests that some listeners detect few anomalies while  
 585 others consider that nearly one third of the words presented in the experiment  
 586 were produced with anomalies. Consequently, we raised the question whether  
 587 listeners’ responses were consistent or whether their subjectivity may have  
 588 an influence on the results presented in the previous sections.

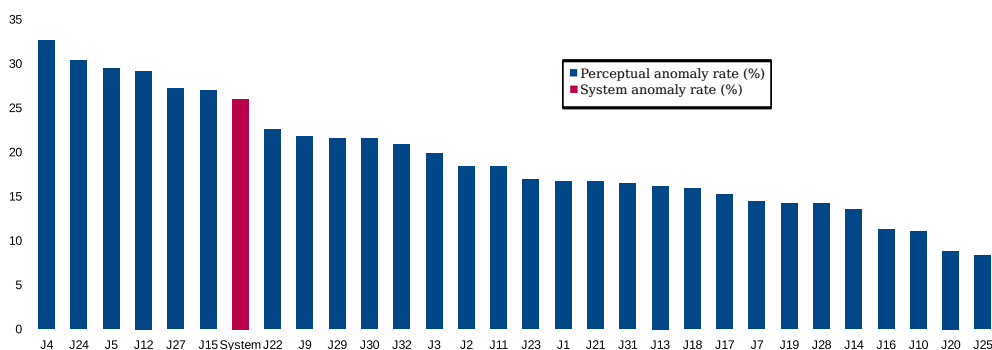


Figure 6: Anomaly rate (%) per jury member (perceptual, blue bars) and for the system (red bar).

589 In order to check if this jury of 29 subjects was consistent, we decided to  
 590 extract a group of 7 participants from the rest of the jury (jury members J3,  
 591 J5, J9, J22, J28, J30 and J32). This group, containing 2 speech therapists and  
 592 5 final-year speech therapy students, presented both higher agreement rates  
 593 with the system than the rest of the jury and contained more homogeneous  
 594 members in terms of annotation tendencies.

595 Figure 7 depicts the distribution of *AG\_targetAnomaly*, *AG\_targetNormal*  
 596 and *AG\_nonTargetNormal* measures when computed on the different test  
 597 categories (“obvious segments”, “ambiguous segments”, “false negatives” and  
 598 “false positives”) for the sub-jury.

599 We observed that the same pattern observed earlier on the complete jury (fig-  
 600 ure 4) is maintained for the sub-jury. Nonetheless, and considering *AG\_targetAnomaly*  
 601 measure, we note a higher System-Jury agreement rates when considering the  
 602 sub-jury reaching 95.4% and 64.0% for “obvious segments” and “ambiguous  
 603 segments” respectively compared to 78% and 58% for the complete jury on  
 604 both test categories respectively.



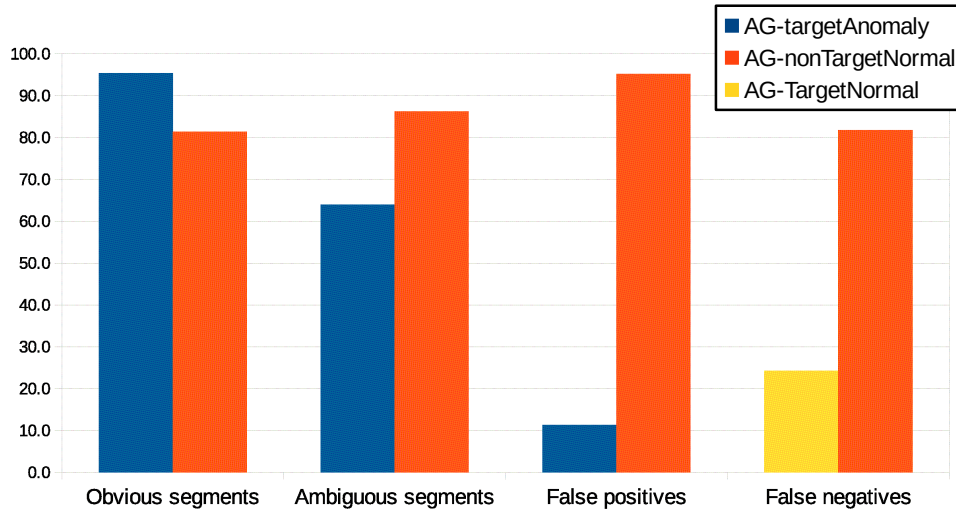


Figure 7: System-Jury agreement rates (%) on automatically detected abnormal words (*AG\_targetAnomaly*), normal target words (*AG\_targetNormal*) and normal non-target words (*AG\_nonTargetNormal*) per test sequence category for the sub-jury.

605 However, quite the opposite behavior was observed in the "false nega-  
 606 tives" test category where *AG\_targetNormal* for the sub-jury is only 24.2%  
 607 whereas it reaches 30% for the complete jury. This behavior can be explained  
 608 by the fact that the chosen sub-jury tended to detect more anomalies than  
 609 the overall tendency which favors the system when studying anomalies de-  
 610 tected automatically ("obvious segments", "ambiguous segments" and "false  
 611 positives") but disadvantages it when considering abnormal segments that  
 612 the automatic approach failed to detect ("false negatives").

613 Finally, comparable *AG\_nonTargetNormal* rates were computed for both  
 614 juries in the different test categories and for the sub-jury reached 81.4%,  
 615 86.2%, 81.8% and 95.1% for the "obvious segments", "ambiguous segments",  
 616 "false negatives" and "false positives" categories respectively.

## 617 5. Discussion

### 618 5.1. The automatic approach quality

619 The results presented in section 4 confirm the capacity of the studied  
 620 automatic approach in the detection of anomalies in dysarthric speech pro-  
 621 duction. Also, the use of different test sequence categories made the analysis

622 of the approach behavior in various contexts possible. Indeed, when the  
623 anomalies are easily identified perceptually ("obvious segments"), the auto-  
624 matic approach has also proven its capacity in the detection of such segments  
625 (78% *AG\_targetAnomaly*).

626 Despite the observed severity underlined by the low *AG\_targetAnomaly* ob-  
627 tained in the "false positives" category, the automatic approach is also able  
628 to demonstrate moderate and non-arbitrary behavior as supported by its  
629 high *AG\_nonTargetNormal* reaching 88% on all test sequences.

630 In addition, the behavior observed concerning the "ambiguous segments"  
631 is of major interest and encouraging. Indeed, remember that in this case  
632 the presence of anomalies is much harder to identify and is more often ques-  
633 tioned, which leads to a high variability observed among the jury members.  
634 Here, the expert jury agreed with the automatic decision in 58% of the cases  
635 "only", which is near the random threshold. Therefore, the whole jury con-  
636 firmed the ambiguity of these segments. However, it is important to note  
637 that the system decisions are binary and similar to each jury's response,  
638 taken individually. The responses of the expert jury are considered to be  
639 "random" because of the comparison of the 29 responses. They are also  
640 random because the stimuli (speech sequences) are ambiguous. Indeed, the  
641 degree of phonetic deviation produced by patients is gradual and not binary.  
642 Consequently, the system should be considered an isolated jury, as reported  
643 in Figure 6 in which, that system proves to be one of the severest juries, but  
644 clearly not the severest.

645  
646 From a clinical application point of view, the behavior of the automatic  
647 approach could be preferred compared with humans since it will be forced  
648 to make a binary decision (normal or abnormal) on such ambiguous speech  
649 sequences, while allowing clinicians to benefit from the reproducibility of such  
650 decisions. Furthermore, the severity of the automatic approach, potentially  
651 considered to be a limitation, yields the benefit of detecting the majority of  
652 the potential anomalies, requiring a more perceptual and acoustical in-depth  
653 analysis, which could finally be viewed as a key strength.

## 654 5.2. *Inter-jury variability and judgment tendency*

655 As expected, the jury's responses show some variation in the perception  
656 of anomalies. Nevertheless, despite this variability, the responses of listeners  
657 remain consistent and have similar tendencies. Indeed, the analysis of the  
658 responses of the sub-jury shows that a selection of homogeneous listeners

659 provides similar results to that of the set of 29 more heterogeneous listeners.  
660 This suggests that the ability of listeners to detect more or less anomalies  
661 does not affect the coherence of the results and the global tendencies observed  
662 in the perceptual evaluation.

663 Nevertheless, we probably should provide some interpretation of the vari-  
664 ation observed in listeners' responses. This variability may be interpreted  
665 as a consequence of the difficulty of the task proposed to the jury. Indeed,  
666 listeners were asked to focus their attention on a single word which may be  
667 produced with or without an anomaly. This is not the way clinicians usu-  
668 ally evaluate their patients. Nor is it the way humans perceive speech. The  
669 process of speech perception is more holistic and requires a large context of  
670 speech in order to evaluate if it is distorted or not. Focusing on a specific  
671 item is a very difficult task for listeners.

672 Moreover, listener judgments seem to be influenced by the severity of the  
673 patients. In table 2, we note that for "ambiguous segments" (for which the  
674 agreement between the experts and the system is low), the responses of the  
675 expert jury depend on the specificity of populations. For CTRL and PD  
676 speakers (low severity) the *AG\_nonTargetNormal* is very high, while for  
677 ALS speakers (higher severity) it is lower.

678 Moreover, in table 6, *AG\_nonTargetNormal* rates decreased for the sever-  
679 ity groups 2 and 3. This means that normal speech segments (according to  
680 the automatic system and the two human annotators) produced by highly  
681 dysarthric speakers, are more frequently perceived as abnormal than seg-  
682 ments produced by control speakers or mildly dysarthric patients due to their  
683 contextual (pathological) information. Thus, we assume that anomalies are  
684 more often detected in words when speech sequences sound pathological.

685 Consequently, both the subject's judgment and system anomaly detection  
686 seem to differ in two dimensions: first, the system is able to focus on short  
687 units to detect anomalies (phones, syllables, words) while subjects are ac-  
688 customised to perceiving speech sounds amongst a larger linguistic context in  
689 order to take their decision; second, humans cannot avoid processing contex-  
690 tual information about the speakers (i.e. pathological specificity) and their  
691 decision is affected by this information, while the system does not take into  
692 account the information on speakers' specificity.

693 Finally, despite these differences, the results on "obvious segments" category  
694 show a strong agreement between the jury and the system. This agreement  
695 confirms the value of the automatic system and its ability to highlight speech  
696 anomalies in a clinical context. We noted that the system behavior is similar

697 to the most severe juries which is a positive result since the system does not  
698 miss anomalies. Consequently it provides a very useful tool to complement  
699 and refine the judgment of clinicians. Moreover, it provides useful data for  
700 acoustic studies on phoneme distortions in a pathological context.

## 701 6. Conclusion

702 In this paper, an original perceptual evaluation protocol of speech se-  
703 quences, in the specific context of disordered speech, is proposed. Initially,  
704 the aim of this protocol and its specific design was to analyze and compre-  
705 hend the behavior of an automatic anomaly detection system on dysarthric  
706 speech, by comparing the automatic annotations with those of an expert jury  
707 stemming from a perceptual evaluation. To reach this goal, speech sequences  
708 used for the perceptual evaluation were pre-classified into four different cat-  
709 egories, mostly reflecting the unsuitable behavior of the automatic system.  
710 Different agreement rates between the expert jury’s decision and the auto-  
711 matic system were examined according to different observation contexts.

712 As detailed in the paper, various results confirm the capacity as well as the  
713 relevance of the automatic approach in detecting the presence of anomalies  
714 in dysarthric speech (high *AG\_targetAnomaly* rates on ”obvious segments”).  
715 By contrast, the low *AG\_targetAnomaly* rate computed over the ”false posi-  
716 tives” category confirms the approach tends to be more severe than human  
717 experts and requires more analysis on these segments in order to identify  
718 causes of this over-detection by the system. Experimental results also high-  
719 light that, even on the more nuanced anomalies (”ambiguous segments”), the  
720 expert jury agreed with the automatic approach decisions nearly half of the  
721 time. In this way, hypotheses motivated by the limitations recognized in the  
722 literature of the perceptual evaluation [34, 35] and by the high inter-jury vari-  
723 ability observed during this particular evaluation were advanced to explain  
724 this behavior. Besides, this analysis reveals the main differences between the  
725 automatic and human process for the targeted detection task in terms of the  
726 size of the acoustic units and contextual information.

727  
728 Unlike other fields of application, supervised automatic speech processing  
729 involved in the task of anomaly detection relies on annotated training data,  
730 for which the correctness can be questioned, as seen with the ambiguous cases  
731 this study focused on. In fact, acoustic models used for the specific anomaly  
732 detection task might be trained on doubtful annotated data. Similar remarks

733 could be made about the decisions of the system. Faced with some ambiguous  
734 cases, it is difficult to know whether the system responds correctly given that  
735 an expert jury may agree with it half of the time. Based on these remarks,  
736 it seems increasingly essential :

- 737 • to question the veracity of decisions taken by the expert jury, which  
738 can be used either for the model training, or for the automatic system  
739 evaluation as well as decisions taken by the automatic approach to be  
740 able to measure its performance evaluation ;
- 741 • to know how to interpret these decisions taken by both humans and the  
742 system, and the way they might interact to decide whether the system  
743 is robust enough to be used in a clinical practice for instance.

744 The authors also suggest raising a more primitive question : considering all  
745 the limitations of perceptual evaluation reported in the paper, should an au-  
746 tomatic approach replicate its results and what place should be envisaged in  
747 future investigations between supervised (relying on human annotations) and  
748 semi- or unsupervised approaches for the specific task of anomaly detection,  
749 still considered a crucial step for clinicians in their evaluation of disordered  
750 speech ?

## 751 **7. Acknowledgments**

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863 **8. Appendix A: Instruction list**

864 You will hear recordings of read texts in which sequences of one or more  
865 words have been extracted.

866 The speech produced during these readings may eventually present patho-  
867 logical deviations.

868 We ask you to judge whether the words of this sequence are deviant or not,  
869 knowing that each of the sequences can be altered in part, totally, or not at  
870 all.

871

872 You can listen to each sequence up to three times by clicking on the small  
873 speaker box.

874 However, if a single listening is sufficient to give your answer, you can go  
875 directly to the next sequence by clicking on the "next" box.

876

877 By default, each word appears as "normal", if one (or more) of them  
878 seems deviant, tick in the "deviant" line, the box(es) under the word(s).

879

880 *Warning, the sequences have been cut from a continuous speech stream:*  
881 *The beginnings and/or ends can sometimes be abrupt, please do not take them*  
882 *into account.*

883

884 The experiment should last between 30 and 40 min.

885 There will be a short training session to familiarize you with the task. There  
886 are no right or wrong answers, what interests us is your judgment.