A real-time algorithm for acoustic monitoring of ingestive behavior of grazing cattle

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Abstract

Assessment of both grazing behavior and herbage intake are two very difficult tasks that can be concurrently accomplished by means of accurate detection, classification and measurement of grazing events such as chews, bites and chew-bites. It is well known that acoustic monitoring is among the best methods to automatically quantify and classify ingestive and rumination events in grazing animals. However, most existing methods of signal analysis appear to be computationally complex and costly, and are therefore difficult to implement. In this work, we present and test a novel analysis system called Chew-Bite Real-Time Algorithm (CBRTA) that works fully automatically in real-time to detect and classify ingestive events of grazing cattle. The system employs a directional wide-frequency microphone facing inwards on the forehead of animals, and a coupled signal analysis and de-

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cision logic algorithm that measures shape, amplitude, duration and energy of sound signals to iteratively detect and classify ingestive events. Performance and validation of the CBRTA was determined using two databases of grazing signals. Signals were recorded on dairy cows offered either, natural pasture ($N = 25$), or experimental micro-swards in indoor controlled environment ($N = 50$). The CBRTA exhibited a simple linear complexity capable to execute 50 times faster than real-time and without undermining overall recognition rate and accuracy when signals were processed at 4 kHz sampling frequency and 8 bits quantization. Furthermore, CBRTA was capable to detect ingestive events with a 97.4% success rate, while achieving up to 84.0% success for their classification as exclusive chews, bites or composite chew-bites. The methodology proposed with CBRTA has promising application in embedded microcomputer systems that necessarily depend on fast real-time execution to minimize computational load, power source and storage memory. Such a system can readily facilitate the transmission of processed data through wireless network or the storage in an onboard device.

Keywords: Acoustic monitoring, cattle grazing behavior, jaw movement classification, real-time execution, signal processing.

1. Introduction

Accurate monitoring of livestock grazing behavior is necessary to ensure that most basic requirements of animal health and welfare are met and consistent with practices that can assure sustainable and efficient use of grazing resources. Hence, different efforts have been put into finding most appropriate techniques to measure and monitor diet and feeding behavior of free-

7 grazing animals (Hodgson et al., 1996; Delagarde et al., 1999). One possible
8 and reliable way is through the detection of distinct jaw movements associ-
9 ated with three common basic events: bites, chews and compound chew-bites
10 (Milone et al., 2012). A grazing bite includes the apprehension and severance
11 of herbage, while a grazing or rumination chew includes the crushing, grind-
12 ing and processing of consumed herbage. The chew-bite is a third important
13 grazing event that results from the overlapping of chewing and biting on a
14 same jaw movement. Thus, jaw movements can serve as a reliable measure
15 of distinct grazing and rumination cycles. Furthermore, the quantification of
16 rumination chews could provide rich information on the ruminal fermenta-
17 tion of fiber and correlated changes in rumen pH (Sauvant, 2000). Likewise,
18 herbage intake rate appears to depend on trade-offs between ingestive bites,
19 chews and chew-bites, and the monitoring of these events could therefore
20 inform on the ability of grazing herbivores to modulate changes in intake
21 rate (Laca et al., 2000). While the number and characteristics of grazing and
22 rumination events vary according to several plant, animal and environmen-
23 tal factors, they could be monitored as indicators of animal health, welfare
24 or nutritional status (De Boever et al., 1990). To the best of our knowl-
25 edge, only few studies have been focused on developing automated systems
26 to monitoring changes in grazing and rumination.

27 One plausible approach to measure feeding behavior is acoustic monitor-
28 ing. Alkon and Cohen (1986) and Alkon et al. (1989) used acoustic bioteleme-
29 try to study the feeding behavior of porcupine. Laca et al. (1992) instru-
30 mented an inward-facing microphone on the forehead of steers to register
31 stronger and readily distinguishable sounds of bites, chews and chew-bites.

32 Consequently, acoustic monitoring proved to be a more effective methodology
33 to discriminate sensitive differences in feeding and rumination than previous
34 jaw recorders or visual observation methods (Ungar and Rutter, 2006), and
35 since then it has been increasingly applied as a research tool to study different
36 aspects of grazing behavior in sheep and cattle (Galli et al., 2006, 2011).

37 Broad application of acoustic monitoring continues to depend on suit-
38 able algorithms for automatic recognition of sound signals associated with
39 chewing and biting. Milone et al. (2009) used concepts of automatic speech
40 recognition and Hidden Markov Models (HMM) to develop an algorithm
41 for both detection and classification of chewing and biting. The algorithm
42 successfully detected 89%, 58%, and 56% of chews, bites and compound
43 chew-bites in grazing sheep, respectively. Galli et al. (2011) further tested
44 this algorithm to demonstrate the feasibility of using acoustic variables to
45 estimate herbage dry matter intake in grazing sheep. Subsequently, Milone
46 et al. (2012) developed a new algorithm that hereafter will be referred as
47 CBHMM (Chew-Bite Hidden Markov Model) that extended upon previous
48 HMMs. The CBHMM was developed for both detection and classification of
49 chews, bites and chew-bites, in grazing cattle; obtaining up to 85% successful
50 recognition rate.

51 In an independent development Clapham et al. (2011) adapted the use of
52 SIGNAL software (Engineering Design, Berkeley, CA) for analysis of grazing
53 sounds in cattle. The software was operated on a careful calibration to detect
54 bites in the band of 17 kHz to 22 kHz, and on a high-pass filter with cutoff
55 frequency at 600 Hz to attenuate background noise. The software detected
56 bites with a 95% confidence, but it seems to demand careful and site-specific

57 calibration before it can be used with different animals, pastures or exper-
58 imental conditions. The capacity of the recording device and power source
59 were among other limitations of the proposed system.

60 Navon et al. (2013) implemented an algorithm that used a machine-
61 learning approach to analyze time-domain features (i.e., shape, intensity,
62 duration and sequence of events) of ingestive sounds in grazing cattle. The
63 procedure eliminated the need of calibrations and allowed a detection of in-
64 gestive events with a 94% correct and 7% false identification. More recently,
65 Tani et al. (2013) applied pattern recognition techniques to iteratively mea-
66 sure eating and ruminating events collected by a single-axis accelerometer.
67 The recognition patterns were defined in frequency domain and used to iden-
68 tify and classify likely eating and rumination events. Without previous cal-
69 ibration, recognition results were similar to previous analytical procedures
70 used by Clapham et al. (2011) and Navon et al. (2013) . However, likely lim-
71 itations of the methodology were associated with the spectral similarities be-
72 tween rumination and eating signals, presence of non-stationary background
73 noise, and high computational cost associated with the analysis of signals
74 sampled at high frequency.

75 Although several of the previous instrumentation and analytical proce-
76 dures have shown good performance for detection of signals associated with
77 eating and/or rumination, few of them offered possibilities to accurately clas-
78 sify exclusive bites, chews and chew-bites, which is a necessary condition for
79 reliable measures of grazing behavior and even for estimation of herbage in-
80 take by means of acoustic methods. Furthermore, most if not all of previous
81 methodologies deal with high quality and long duration signals (hours or

82 days) that can demand collection, recording, storage, transfer and analysis
83 of data by means of computationally complex and costly procedures, that can
84 quickly undermine their application as fast, efficient and timely monitoring
85 systems.

86 The main objectives of the present work were: 1) to develop a novel
87 algorithm called CBRTA (Chew-Bite Real-Time Algorithm) that can be ex-
88 ecuted in real-time for automatic and efficient identification and classification
89 of chews, bites and chew-bites, 2) to provide an analysis of the computational
90 complexity of CBRTA, 3) to examine the operational performance of CBRTA
91 as a function of modifications in algorithm parameters, and, 4) to provide a
92 validation of CBRTA for both detection and classification of ingestive events
93 in cattle by using two databases of acoustic monitoring of dairy cows grazing
94 either outdoor temperate pasture or micro-swards in indoor controlled envi-
95 ronment. Outdoor grazing environments inevitably introduce some level of
96 unpredictable and variable background noise that can readily interfere with
97 the acquisition and analysis of chewing and biting signals. We aimed there-
98 fore to deal with commonly encountered levels of such noises by combining
99 passive isolation (directional microphones with isolation material) and basic
100 signal processing.

101 **2. The algorithm**

102 The design goal was the achievement of an algorithm that can combine
103 high performance for detection and classification of sound events with low
104 computational cost, which is a necessary condition to allow real-time execu-
105 tion of the algorithm in portable embedded systems. To achieve this goal,

time-domain instead of transformed-domain (frequency, time-frequency) analysis was implemented to avoid high computational load of signal analysis.

2.1. General description

Signals associated with an exclusive chew (Figure 1a), composite chew-bite (Figure 1b) or exclusive bite (Figure 1c) have readily distinguishable properties.

Figure 1: Examples of typical acoustic events produced by jaw movements and their correspondent features: (a) chew, (b) chew-bite and (c) bite. Within each row, top-down: raw acoustic signal, computed envelope, sign of envelope slope, maximum intensity and duration are shown.

Therefore, the shape, maximum intensity and duration of sounds were isolated to discriminate among the bites, chews and chew-bites. The shape

114 of a jaw movement is characterized by changes in both the intensity and sign
115 of the envelope slope (Figure 1). The sign (either positive or negative) of
116 the envelope slope changes one or two times for chews and bites and more
117 than two times for composite chew-bites. The three jaw movements also
118 produce sounds with distinguishable maximum intensity that remains low
119 for chews and high for bites, and changes from low to high for composite
120 chew-bites. Finally, bites, chews and composite chew-bites, have a defined
121 duration, which is shorter for chews and bites and longer for composite chew-
122 bites (Figure 1).

123 Sound properties were then used by the algorithm to complete two suc-
124 cessive tasks, event detection and event classification, respectively. For the
125 detection task, the algorithm detects the region of the sound envelope that
126 shows the occurrence of a possible jaw movement. This detection is carried
127 out through the identification of characteristic peaks in the sound envelope
128 using an adaptive threshold. For the classification task the algorithm uses a
129 simple set of rules to compute and compare the shape, intensity and duration
130 of a detected event to a given threshold value.

131 For implementation purposes, the completion of the two tasks can be
132 thought as a set of five successive stages, where the first four stages are used
133 to complete the event detection task, while the event classification task is
134 performed during the last stage, as follows.

135 **Stage 1 - Envelope computation:** One basic requirement for the im-
136 plementation of the algorithm is the envelope computation, which is decom-
137 posed into three steps: i) signal rectification, ii) signal filtering and iii) signal
138 subsampling. In the first step the absolute value of signal samples is com-

Figure 2: Example of a 15s sound track with correspondent signals generated by the processing algorithm: (a) original raw signal, (b) sound envelope computation, (c) event detection, (d) slope sign, (e) maximum amplitude, and (f) duration of detected events.

139 puted at the original sampling frequency. In the second step, the signal is
 140 filtered using a second-order low-pass Butterworth filter with a bandwidth
 141 of 5.5 Hz, producing the sound envelope. In the third step, a subsample of
 142 the original sound envelope to 100Hz is conducted (Figure 2b). The main
 143 objective of this task is to reduce the computational requirements (load and
 144 computation time) in the subsequent tasks, since this process significantly re-
 145 duces the amount of information to be processed but without compromising
 146 accuracy in the detection and classification of sounds.

147 **Stage 2 - Division of sound into segments:** Short segments have
 148 lower computational resource constraints, are easier to handle, and their use

149 can facilitate the treatment of unexpected events that need special attention.
 150 Such events include intense external noises of short duration and background
 151 noises. The size of segments depends on the computational resources that
 152 are available to implement the algorithm. In a common desktop computer
 153 segments can have a typical duration of 30 s or longer. In an embedded
 154 system with low computational capacity segments should have a smaller size.
 155 Ultimately, segment size depends on the amount of memory available for
 156 signal analysis (minimum size of 2 s).

157 **Stage 3 - Event detection:** The presence of peaks in the sound en-
 158 velope reveals possible target events. Each peak is detected as a change in
 159 the derivative of the envelope. However, to be considered a possible event
 160 it must be higher than given thresholds. The peaks are detected through
 161 the comparison of the sound envelope with a time-varying threshold $T(k)$
 162 (red dashed line in Figure 2c), where k is a time variable. This threshold
 163 is generated by an algorithm that considers both anatomical and behavioral
 164 characteristics of the animal according to the following two rules: i) a min-
 165 imum period of time between two consecutive jaw movements, and, ii) a
 166 maximum duration of jaw movements within a continuous activity (i.e. ru-
 167 minating or grazing). Then, following Christov (2004) the event detection
 168 algorithm uses this criteria to generate the time-varying threshold $T(k)$ with
 169 the following features:

- 170 • **Unresponsive period** (T_U): period of time after detecting an event
 171 in which the algorithm is no longer searching for a new event. It is
 172 computed for each event as a fraction α ($0 < \alpha < 1$) of the average
 173 duration of the last five events detected.

174 • **Maximum period** (T_M): maximum time that an event can last within
 175 the same activity. It is computed for each event as β ($\beta \geq 1$) times the
 176 average duration of the last five events detected.

177 • **Peak expectation threshold** (T_P): minimum value expected for the
 178 next peak intensity (blue dot-dash line in Figure 2c). It is computed
 179 as a fraction γ ($0 < \gamma \leq 1$) of the moving average of the last five peaks
 180 detected in the envelope signal

$$T_P(k) = \frac{\gamma}{5} \sum_{i=1}^5 S_P(j-i). \quad (1)$$

181 where S_P is the peak intensity of an event, and j is an event counter.

182 • **Threshold slew-rate** (ΔT): is the decrease of threshold $T(k)$ once
 183 after the unresponsive period T_U expires, and serves therefore to sig-
 184 nificantly improve the event detection sensitivity. The threshold $T(k)$
 185 only changes during the time period between T_U and T_M , as follows

$$T(k) = T(k-1) - \Delta T, \quad \forall T_U < k < T_M. \quad (2)$$

186 This stage of the algorithm generates a temporary file with correspondent
 187 timestamps to indicate the location of all detected peaks. This peak reference
 188 is then used in subsequent event detection and classification stages to trigger
 189 the analysis of signal properties.

190 **Stage 4 - Properties computation:** This step computes the shape,
 191 maximum intensity and duration of the sound to classify likely candidate
 192 events detected in previous stages. The shape of the event is computed as
 193 the number of changes (NC) in the sign of the envelope slope (Figure 2d).

194 To avoid confusion with noises, the slope is computed only if the magnitude
195 of the sound envelope is bigger than the background noise (NT) detected in
196 the analyzed segment. The maximum intensity of the envelope sound (EA)
197 is computed directly from the absolute value of the signal over a window
198 of time whose length is half of the duration of a typical chew-bite event
199 (Figure 2e). The duration of the event (ED) is determined from the sound
200 envelope by measuring the time period when the sound envelope is bigger
201 than the background noise NT (Figure 2f).

202 **Stage 5 - Event classification:** Using a specific set of rules, based
203 on previously computed properties, each event is classified into one of five
204 categories: chew (C), bite (B), chew-bite (CB), silence (S) or noise (N).
205 Briefly, the algorithm explores the timestamp, NC , EA and ED to detect
206 and classify the events. The algorithm applies a set of rules to find whether
207 a true event has happened or not and, in a positive case, which kind of event
208 has been detected. The set of rules employed by the algorithm are established
209 heuristically from a training data set, under the constraints that the set of
210 rules should be small. The set of decision rules is detailed in Table 1. Each
211 rule specifies the conditions that NC , EA and ED must meet to be classified
212 as C, B or CB, respectively. For example, if NC is greater than 2, EA exceeds
213 NT and ED is greater than 0.3 s, then the detected event is classified as CB.

214 Figure 3 shows the flow diagram of the algorithm, integrating all steps
215 for envelope computation, segmentation, detection and classification of jaw
216 movements. The envelope signal $Sp(k)$ is loaded and analyzed by segments
217 of N samples. When a segment is fully analyzed, the results are saved before
218 analyzing the next segment. In the first stage, the algorithm computes the

Table 1: Rules for jaw movement event classification[†] .

Event	Rule
Chew-bite	if $NC > 2$ and $EA > NT$ and $ED > 0.3[s]$ then $L(j)=CB$
Bite	if $NC \leq 2$ and $EA \geq 0.5 T_P$ and $ED < 0.3[s]$ then $L(j)=B$
Chew	if $NC \leq 2$ $EA > NT$ and $EA < 0.5T_P$ and $ED < 0.3[s]$ then $L(j)=C$

[†] NC is the number of changes in the sign of the slope of sound envelope, EA is the maximum intensity of the envelope, ED is the duration of the event, NT is the background noise threshold and T_P is the peak expectation threshold.

time-varying threshold $T(k)$. Then, it checks if a peak has been detected. If no peaks have been detected, the algorithm assigns the silence label (S) to the event. If a peak has been detected, the algorithm classifies the event by applying rules based on the event properties NC , EA and ED , and by assigning the correspondent label C, B, CB or N.

3. Materials and methods

Acoustic monitoring of grazing dairy cattle was used to test the performance of the algorithm and its software implementation. Signals were recorded on a different duration (in some cases several hours) but for analysis and testing only maximum periods of 5 minutes were considered, given the practical difficulty of labeling aurally longer periods. It was also necessary to establish performance measures for analysis purposes.

3.1. Experimental field conditions for collection of datasets

Two databases were obtained under different grazing conditions, and at different times and locations. The first database included signals of dairy

Figure 3: Flow diagram of the algorithm for event detection and classification.

234 cows grazing temperate pasture and was therefore useful to test the algo-
235 rithm in an outdoor noisy environment. Signals for the second database
236 were collected with dairy cows grazing micro-swards in an indoor controlled
237 experiment. This database was used to further analyze the effect of for-
238 ages (species and height) on the detection and classification capabilities of
239 the algorithm, and to compare the performance of the algorithm against the
240 previous CBHMM methodology developed by Milone et al. (2012).

241 The first database was obtained from an experiment performed at the
242 W.K. Kellogg Biological Station dairy facility of Michigan State University,
243 Hickory Corners, USA, during August of 2014. Protocols for animal handling
244 and care were reviewed, approved and conducted according to the Institu-
245 tional Animal Care and Use Committee of Michigan State University. In this
246 experiment the daily foraging behavior of five multiparous lactating Holstein
247 cows grazing perennial ryegrass/white clover and orchardgrass/white clover
248 dominated pastures were monitored for six days, according to 5 x 5 Latin-
249 square design to control for recording device and cow. This design therefore
250 produced a total of 25 sound tracks of 24h duration. Cows were managed
251 on a robotic milking system with voluntary grazing of pasture using same
252 management protocols described in Watt et al. (2015). These signals were
253 recorded using a SONY ICDPX312 recorder mounted on a cow halter and
254 a directional microphone pressed onto the forehead of the cow. All record-
255 ings were made at 44.1 kHz sampling rate and 16-bit resolution, providing a
256 nominal 22 kHz recording bandwidth and 96 dB dynamic range, and stored
257 in the WAV (Waveform Audio) file format. Hereafter, these recordings will
258 be referred as the Michigan Database (MDb).

259 The second database was the same as used by Milone et al. (2012) for
260 development and testing of the algorithm CBHMM. Briefly, the fieldwork to
261 obtain this database was performed at the Campo Experimental J.F. Villar-
262 ino, Facultad de Ciencias Agrarias, Universidad Nacional de Rosario, Zavalla,
263 Argentina during February 2004. Project protocols were previously evaluated
264 and approved by the Committee on Ethical Use of Animals for Research of
265 the Universidad Nacional de Rosario. Sound signals from dairy cows grazing
266 either **pure** alfalfa or **pure** fescue micro-swards at two heights (tall, 24.5 ± 3.8
267 cm, or short, 11.6 ± 1.9 cm) were recorded individually in grazing sessions
268 conducted over a 5-day period. Forage species were selected because they dif-
269 fer in sward structure and neutral detergent fiber content (alfalfa, 360 ± 11
270 g/kg and fescue, 631 ± 6 g/kg), which are factors that have direct influence
271 on chewing sounds (Duizer, 2001). Two 4–6 year-old lactating Holstein cows
272 weighing 608 ± 24.9 kg, previously tamed and trained, were used. A wire-
273 less microphone (Nady 151 VR, Nady Systems, Oakland, CA, USA) was
274 randomly assigned to animals each day. The microphone was placed facing
275 inwards on the forehead and was protected by rubber foam (Milone et al.,
276 2009). The distance between the wireless microphone and the receiver was
277 2–3 m. Micro-swards were hand-constructed using plants in pots that were
278 firmly attached to a baseboard placed inside a barn. Behavior was recorded
279 with an analog video camcorder (Sony CCD-TR517), and then coded in MPG
280 format at 25 frames per second. The sound from the wireless microphone was
281 recorded on the tape soundtrack (16 bits, 44.1 kHz). A total of 50 grazing
282 sessions were recorded: 15 from tall alfalfa, 11 from short alfalfa, 12 from
283 tall fescue and 12 from short fescue. On average, for each pasture/height the

284 signals contained approximately 13 min of recording and around 800 events
285 (13% bites, 64% chews and 23% chew-bites). Hereafter, these recordings will
286 be referred as the Rosario Database (RDb).

287 All signals were labeled aurally by experts in animal behavior to identify
288 and classify individual events (C, B, CB, S, N) during grazing. **The labeling**
289 **process was done by one expert, and the result was checked by**
290 **another expert. In most of the cases experts largely agreed with**
291 **the labeling of signals, but when there was disagreement, both**
292 **experts worked together to provide a final decision.** This labeling
293 was used as control reference for comparison and testing of the performance
294 of the algorithm. In the case of signals belonging to MDb, two periods
295 of 5 minutes were extracted and labeled from each 24h sound track. **The**
296 **signals were randomly selected within a grazing period, because**
297 **during this activity the three types of events considered can be**
298 **found.** Each period contained approximately 350 events (25% bites, 48%
299 chews and 27% chew-bites). One of the periods was used to analyze the
300 effect of parameters while the other one was used for evaluation purposes.
301 A similar data partition was made for signals belonging to RDb. For each
302 grazing session, 50% of signals were used to analyze the effect of parameters,
303 while the remaining 50% was used for evaluation purposes.

304 3.2. *Performance measures*

305 Valid comparisons between events recognized and classified by the algo-
306 rithm and their corresponding reference of aurally labeled events depends
307 on the correct synchronization of both event sequences. To solve this prob-
308 lem, the HTK¹performance analysis tool HResults was used, which is based

309 on a dynamic programming-based string alignment procedure (Young et al.,
310 1997).

311 The outputs of this tool were: i) the number of deleted events (D), **which**
312 **are false negatives**, ii) the number of substituted events (S), **which are**
313 **misclassified events**, iii) the number of inserted events (I), **which are**
314 **false positives**, and iv) the total number of events (T) in the reference
315 transcription **provided by the experts. An example of these defini-**
316 **tions is shown in Table 2: the first bite of the recognized sequence**
317 **is a substitution (S) because the real event is a chew; the second**
318 **chewbite is an insertion (I) because there is no event in the real**
319 **sequence; and the second chew in the reference sequence has not**
320 **been recognized so it is a deletion (D).**

Table 2: Example of sequence alignment for performance measurement.

Reference seq.:	chewbite	chew	<u>chew</u>	bite	chew		bite	bite
Recognized seq.:	chewbite	<u>bite</u>		bite	chew	<u>chewbite</u>	bite	bite

321 **Keeping these definitions in mind, the percentage of detected**
322 **events is computed as follows²**

$$\delta\% = \frac{T - D}{T} 100\%, \quad (3)$$

323

324 the percentage number of **events** correctly recognized is given by

²<http://htk.eng.cam.ac.uk/>

$$C\% = \frac{T - D - S}{T} \cdot 100\%, \quad (4)$$

325

326 and the accuracy is computed by

$$A\% = \frac{T - D - S - I}{T} \cdot 100\%. \quad (5)$$

327 Performance of CBRTA for recognition of C, B, CB, S or N was assessed
 328 using exploratory analysis of sensitivity. This analysis computed the cor-
 329 respondent recognition rate $C\%$, accuracy $A\%$ and computational time as
 330 a function of changes in the following key parameters: i) the sampling fre-
 331 quency, ii) quantization level, iii) cut-off frequency of the detector filter, and
 332 iv) subsampling frequency. The effectiveness of CBRTA for detection of in-
 333 gestive events (C, B, CB) was determined **considering false negatives in**
 334 **the computation, but no substitutions**³. The effectiveness of CBRTA for
 335 classification of ingestive events (C, B, CB) was determined in two ways. For
 336 the MDb database, a cross-way validation was conducted in order to demon-
 337 strate robustness. For this comparison, the CBRTA was fitted with the best
 338 set of parameters for the MDb and RDb database, respectively. **By best**
 339 **set of parameters we means a set of parameters that provides the**
 340 **highest recognition rate with the highest accuracy**. Then, the classi-
 341 fication by CBRTA fitted with the best set of parameters for MDb database
 342 [CBRTA (MDb)] was compared to the correspondent classification of CBRTA

³While this computation does not include insertions (false positives), these were quan-
 tified in the present analysis.

343 fitted with the best set parameters for the RDb database [CBRTA (RDb)].
 344 For the RDb database, the CBRTA was compared to the CBHMM algorithm
 345 of Milone et al. (2012). This comparison was decided for two reasons. The
 346 CBHMM is the only other available method that makes a distinct classifi-
 347 cation of C, B and CB, and, the CBRTA and CBHMM are both originally
 348 fitted to the same RDb database, thus offering a direct unbiased comparison
 349 of methods. On the other hand, the application of the CBHMM method on
 350 a different database could be wrong, because the models would need to be
 351 adapted to the new recording conditions. Also, it is important to note that
 352 to train and evaluate the CBHMM, a hold-out cross-validation method was
 353 used (Duda et al., 2001), while in the present CBRTA parameterization is
 354 done using a subset of RDb data not further used for testing purposes. The
 355 CBRTA was implemented using MATLAB R2010b for evaluation purposes.
 356 Thereafter, the analysis included the testing of i) algorithm complexity,
 357 ii) computational performance, and iii) validation of CBRTA for both the
 358 automatic detection and classification of ingestive events in grazing dairy
 359 cattle. The computational complexity was modeled for each computational
 360 task as the function of the number of samples n to be processed each sec-
 361 ond. For more exhaustive analysis, the computational cost of CBRTA was
 362 compared to the CBHMM algorithm proposed by Milone et al. (2012).

³This is because there are no substitutions in a detection problem, since we are only
 interested in whether an event has occurred or not, regardless of its type. Instead, the
 classification stage of events should consider substitutions.

363 4. Results

364 4.1. Complexity analysis

365 The computational cost for each step of the CBRTA algorithm evalu-
366 ated as function of the number of samples n to be processed each second is
367 shown in Table 3. This analysis considered a filtering task applied as second
368 order **infinite impulse response (IIR) filter**. The total number of oper-
369 ations per second $f_{CBRTA}(n)$ required to execute the CBRTA algorithm was
370 $f_{CBRTA}(n) = 13n + 3700$. As shown in Table 3, only the first three tasks
371 (i.e., rectification, filtering and subsampling) will depend on the sampling
372 frequency of the input signal. After subsampling (Stage 1), the signal pro-
373 cessed by the remaining tasks has a constant sample rate (100 samples/s).
374 Therefore, the remaining tasks will be independent of the audio sample rate.
375 For example, the computation of the envelope slope requires the subtraction
376 of two consecutive samples for computation of its sign, which involves two
377 operations per sample. Similarly, the classification of events involves five
378 comparisons to check whether the predefined classification conditions are
379 met or not. A more detailed description of the complexity analysis for the
380 CBRTA algorithm is provided in Appendix A. This analysis shows a linear
381 computational complexity for CBRTA. A comparative analysis of complexity
382 on the CBHMM algorithm developed by Milone et al. (2012) is summarized
383 in Appendix B. This analysis shows a superlinear complexity for CBHMM.

384 4.2. Effect of parameters on system performance

385 Figure 4 shows the effect of sampling frequency on the performance of
386 the algorithm (recognition rate and accuracy) and the corresponding com-

Table 3: Number of operations per second of the CBRTA algorithm for detection and classification of jaw movement events.

Stage	Task	Operations/s
1	Signal rectification	$2n$
1	Signal filtering	$9n$
1	Signal subsampling	$2n$
2	Samples buffering	100
3	Threshold generation	900
3	Event detection	100
4	Envelope slope computation	200
4	Maximum signal	100
4	Event duration computation	200
5	Silence rule	100
5	Chew-bite rule	500
5	Bite rule	500
5	Chew rule	500
5	Noise rule	500

387 putational time for the MDb database. The recognition rate and accuracy
 388 remained high (around 80%) over wide range of frequencies (from 2 kHz to
 389 11 kHz) and declined for frequencies that were outside of this range. This
 390 phenomenon can be explained by the fact that for sampling frequencies be-
 391 low 2 kHz the signal/noise ratio is degraded because important components
 392 of the signal are filtered out. In a similar way, once the sampling frequency
 393 goes beyond 11 kHz, the amount of noise processed by the algorithm in-
 394 creases, further reducing and degrading the overall signal/noise relationship.
 395 However, in the range of frequencies from 2 kHz to 11 kHz, the information
 396 and noise processed by the algorithm remains unchanged, keeping the overall
 397 signal/noise relationship constant.

Figure 4: Algorithm recognition rate and accuracy and corresponding computational time as a function of sampling frequency for frames of 5-minute duration ($N=25$).

398 The linear dependency of the computational time with sampling fre-

quency is shown in Figure 4. At a sampling frequency of 4 kHz the algorithm had reasonably good compromise between performance (recognition rate and accuracy) and computational time. In this sense, the algorithm proved to be capable of processing signals 50 times faster than real-time or 300 s (5 minutes) of sound signal in 6 s (Figure 4). This means that in a practical application the algorithm is capable to analyze 50 minutes of acoustic data per minute in a standard desktop computer.

Figure 5: Algorithm recognition rate and accuracy, and corresponding computational error as a function of quantization level (computed as word length) for frames of 5-minute duration ($N=25$).

Figure 5 shows the effect of quantization level (or word length representation) on the performance of the algorithm (recognition rate and accuracy) for the MDb database. The recognition rate and accuracy remained high

409 (around 80%) for a quantization level of 8 bits or more. This phenomenon
 410 can be explained by the fact that the quantization error, **measured in terms**
 411 **of the mean square error (MSE) between the signal represented by**
 412 **data of a given word length (resolution) and the signal represented**
 413 **by data of the longest word (16 bits), is almost zero** for ingestive
 414 sound data codified with 8 bits or more.

Figure 6: Algorithm recognition rate and accuracy as a function of cut-off frequency in envelope detector filter for frames of 5-minute duration (N=25).

415 Figure 6 shows the effect of the cut-off frequency of the envelope detector
 416 filter on the recognition rate and accuracy for the MDb database. Both,
 417 recognition rate and accuracy improved as the cut-off frequency of the fil-
 418 ter increased from 3 Hz to 5 Hz. A correct recognition rate over 75% and

419 accuracy over 70% was observed in the frequency range between 5 Hz and
 420 6 Hz. Beyond 6 Hz, both recognition and accuracy declined. These phe-
 421 nomena can be explained by the fact that enlarging the bandwidth of the
 422 filter at low frequencies increases the amount of information processed by
 423 the algorithm, thereby augmenting the overall signal/noise relationship and
 424 the performance of the algorithm. However, once the cut-off frequency goes
 425 beyond the 6 Hz, the information remains constant, the amount of noise pro-
 426 cessed by the algorithm increases, and the overall signal/noise relationship
 427 and performance of the algorithm decreases.

Figure 7: Algorithm recognition rate and accuracy as a function of subsampling frequency for frames of 5-minute duration.

428 Figure 7 shows the effect of the subsampling frequency on the algorithm
 429 recognition rate and accuracy. Both, recognition rate and accuracy were in-

crementally improved with increases in subsampling frequency up to 100 Hz. Beyond this subsampling frequency, the recognition rate remained steady while the accuracy showed a gradual decay. Increasing the subsampling frequency the amount information processed by the algorithm increases, improving the overall signal/noise relationship. However, once the subsampling frequency goes beyond the 100 Hz, the useful information remains constant and the overall signal/noise relationship does not suffer further change.

The algorithm performance analysis for the RDb database rendered a slightly different trend (data not shown). Best recognition rate and accuracy was observed at sampling frequencies between 2 kHz and 4 kHz. With respect to the filter cut-off frequency, the best results were observed at 3.5 Hz, where highest recognition with high accuracy was detected. Moreover, similar recognition performance was obtained at cut-off frequencies of 4 Hz and 5 Hz, but with lowering accuracy. Regarding the subsampling frequency, the best performance was observed at 100 Hz, similarly to MDb database. Also a sampling frequency of 2 kHz rendered lower overall computational cost. **The differences between the parameters of the algorithm obtained for each database are primarily due to differences between the characteristics (frequency response and steady state gain, among others) of microphones used to record the databases.**

4.3. *Event detection and classification*

As can be seen in Figure 3, when ingestive sounds are processed, two different task can be performed: i) detect the existence of an ingestive event within the record without identifying its type,

455 and ii) classify the ingestive event by identifying the type of event
456 detected. Clearly, the detection task is simpler and more accurate
457 than the classification task, since it requires fewer information.

458 For the algorithms considered in this paper the overall detection of in-
459 gestive events was 97.4%, because of the existence 2.6% of deletions
460 (false negatives). Also it was observed 1.4% of insertions (false pos-
461 itives). Regarding event classification, the CBRTA algorithm clearly distin-
462 guished among types of jaw movements in both MDb and RDb databases. In
463 Table 4 the classification of ingestive events for the MDb is presented. The
464 CBRTA algorithm shows an average recognition rate of 84.0% of the total
465 events for CBRTA (MDb) and an average recognition rate of 79% of the total
466 events for CBRTA (RDb). Therefore, the results for event classification were
467 lower than event detection rate by an average of 15%. For both CBRTA
468 (MDb) and CBRTA (RDb) sets of parameters the algorithm achieved good
469 event classification rates, demonstrating ability for scalability and general-
470 ization. Also, Table 4 summarizes the recognition rates for each different
471 event determined for the MDb database. In this table it can be observed the
472 high ability of the algorithm to correctly identify the chew and bite events,
473 regardless of the set of parameters used. However, some degree of confusion
474 between bites and chew-bites was detected for the classification of chew-bites,
475 which may be due to the close similarity of sound properties between both
476 events. We believe that this confusion is less critical at a practical level since
477 B and CB are both ingestive events.

478 Table 5 summarizes the recognition rates for different events for the RDb
479 database. The classification results of CBRTA for this database showed an

Table 4: Percentage of correct and false classification of bites, chews and chew-bites of dairy cows detected by a novel Chew-Bite Real-Time Algorithm (CBRTA) trained and parameterized with a same (MDb) or different (RDb) database[†]. Bold numbers indicate the best results.

Event	Bite		Chew		Chew-bite		Average	
	CBRTA (MDb)	CBRTA (RDb)	CBRTA (MDb)	CBRTA (RDb)	CBRTA (MDb)	CBRTA (RDb)	CBRTA (MDb)	CBRTA (RDb)
Bite	95	94	2	3	3	3		
Chew	8	8	87	91	5	1	84	79
Chew-bite	22	44	8	6	70	50		

[†] Testing database included acoustic records of 5 dairy cows grazing temperate pasture (N=25).

average correct classification rate of 77% of events across all pasture types, while the CBHMM method reached an average of 79% over all pastures. The best results were seen for tall pastures reaching 79% and 78% for alfalfa and fescue respectively, while for short fescue a 77% was obtained. An additional deterioration of 5% in the recognition rate can be appreciated for short alfalfa.

5. Discussion

Most of previous studies of acoustic monitoring in grazing ruminants were focused on the detection of ingestive or rumination events and not in their classification. To the best of our knowledge, the only algorithm that previously focused in both the automatic detection and classification of acoustic grazing events is the CBHMM method developed by Milone et al. (2012). In addition, none of the previous studies made an analysis of the computational complexity of the proposed methodologies. The computational complexity of

Table 5: Percentage of correct and false classification of bites, chews and chew-bites of dairy cows grazing contrasting micro-swards, detected by a former Chew-Bite Hidden Markov Model (CBHMM) or a novel Chew-Bite Real-Time Algorithm (CBRTA)[†]. Bold numbers indicate the best results.

		Bite		Chew		Chew-bite		Average	
		CBHMM	CBRTA	CBHMM	CBRTA	CBHMM	CBRTA	CBHMM	CBRTA
Tall alfalfa	C	79	67	11	18	9	15		
	B	3	2	88	90	9	8	84	79
	CB	2	5	3	11	94	84		
Short alfalfa	C	76	62	16	30	8	8		
	B	5	0	90	94	5	6	65	74
	CB	23	5	15	29	61	66		
Tall fescue	C	83	74	0	21	17	5		
	B	1	1	93	95	7	4	85	78
	CB	1	10	4	33	94	57		
Short fescue	C	90	79	9	14	1	7		
	B	0	1	99	99	1	0	84	77
	CB	2	25	7	32	91	43		

[†] Testing database included acoustic records of 2 dairy cows grazing a factorial set of micro-swards hand-constructed with plants in pots of 2 species (Alfalfa or Fescue) and 2 heights (short or tall), collected in 5-minute recording sessions (N = 50).

493 the algorithm can impose severe limitations for implementation in a system
 494 running in real-time, and this issue becomes relevant when high quality and
 495 long duration (several hours) audio need to be processed. For real-time op-
 496 eration, the algorithm must be able to process a given signal segment before
 497 another segment becomes available. To accomplish this objective, the algo-
 498 rithm must complete at least $f(n)$ fix-point operations per second. For the
 499 range of sampling rates considered in the CBRTA application (from 4 KHz
 500 to 44 KHz), it is easy to find a low cost commercial microprocessor capable to
 501 perform more than the required number of operations. For example, given
 502 a 44 KHz sample rate it is possible to complete the execution of CBRTA
 503 with a Tiva C microcontroller (TivaTM C Series LaunchPad Evaluation Kit,
 504 Texas Instruments Inc., Dallas, TX) using a 10 MHz clock. The processing
 505 speed could be increased further (augmenting the clock frequency), but at
 506 the expense of increasing energy consumption, which is an essential issue in
 507 portable embedded systems.

508 In the present study we carried out a detailed analysis of computational
 509 complexity, performance of the CBRTA algorithm and the CBHMM algo-
 510 rithm to then have a comparative reference of computational complexities.
 511 This analysis showed a linear computational complexity for CBRTA algo-
 512 rithm ($O(n)$), while for the CBHMM method was found a greater superlin-
 513 ear complexity ($O(n \log(n))$). In addition to showing a lower complexity,
 514 the CBRTA algorithm had proven capability of processing grazing signals 50
 515 times faster than real-time. Others authors such as Clapham et al. (2011)
 516 have reached up to 10 times faster than real-time but for algorithms cal-
 517 ibrated for detection of bites alone, excluding therefore two other critical

518 jaw events in grazing animals, exclusive chews and compound chew-bites.
519 Thus, fast processing by CBRTA is a promising result to develop embedded
520 microcomputer applications that depend on real-time analysis.

521 Indeed, a major drawback to process signals real-time on embedded sys-
522 tems is the computational load of the algorithm, since this can determine
523 the requirements of hardware to implement the system. In signal processing,
524 the computational load principally depends on two parameters: i) the sam-
525 pling frequency and ii) the quantization level of the signal. The sampling
526 frequency defines the information flow processed by the system per unit of
527 time (Figure 4) and it plays a key role on the computational load of the algo-
528 rithm (Table 3). The quantization level of the signal defines accuracy of the
529 signal representation and, therefore the word length required by the system
530 to process the information (Figure 5). In this way, quantization defines one
531 aspect of the complexity of the system implementation. Our results showed
532 that CBRTA is capable of achieving reasonable compromise between low
533 computational time and high recognition rate and accuracy with a sampling
534 frequency between 2 kHz and 4 kHz and a quantization of 8 bits. With this
535 likely set of parameters both detection and classification of events rendered
536 results that were similar to previous methodologies but at significantly lower
537 computational cost and running time.

538 The overall performance of CBRTA on event detection was 97.4% across
539 the two databases, which is in the same order of detection rate for algorithms
540 published in the specialized literature. In this sense, Clapham et al. (2011)
541 reported a successful detection of bites of 95%, while Navon et al. (2013) re-
542 ported detection rates for jaw movements of 94% in a low noise environment.

543 Milone et al. (2012) developed an algorithm extending from HMM models to
 544 detect and classify ingestive sounds of cattle (i.e. C, B and CB), reaching a
 545 successful detection rate of 94%. In a similar way, Tani et al. (2013) detected
 546 ingestive and ruminating chewing with approximately a 98% detection suc-
 547 cess. These quantitative results (except the results of algorithm developed
 548 by Milone et al. (2012) that used the same RDb database) are not directly
 549 comparable to the present study because the studies vary in number and type
 550 of events analyzed, duration of records, type and height of pastures, record-
 551 ing procedures and devices, and validation methods. Furthermore, the data
 552 employed in those studies are not available for numerical experimentation.
 553 On the other hand, the remarkable capacity for event detection by **CBRTA**
 554 implies that further classification of ingestive events may not compromise the
 555 ability of an algorithm to efficiently detect ingestive events. Regarding the
 556 event classification stage, to assess the robustness of CBRTA, we decided to
 557 evaluate the performance of CBRTA for two sets of parameters, applied on
 558 the first database (MDb). The recognition rate averaged 84% when CBRTA
 559 was used with the best set of parameters for a partition (not further used
 560 for testing purposes) within the same database, and a performance rate of
 561 79% when it was used with the best set of parameters for a partition (not
 562 further used for testing purposes) of a different database. This result shows
 563 that the algorithm seems to be robust to databases with large differences.
 564 For the second database (RDb), the proposed algorithm achieved a recogni-
 565 tion rate of 77% on average, while the CBHMM method averaged 79.5% over
 566 all pastures. **The best results achieved by CBHMM method is due**
 567 **to the use of a more complex modeling technique (hidden Markov**

models), which allows to capture more accurately the dynamics of the sounds and extract more information. However, this small performance improvement is achieved at expenses of a higher computational cost, as it can be appreciated in Appendixes A and B. Overall, the best results were seen for tall pastures reaching 79% and 78% for alfalfa and fescue respectively, while for short fescue a 77% was obtained. An additional deterioration of 5% in the recognition rate was detected for short alfalfa, which is consistent with previous findings by Milone et al. (2012). A plausible explanation for this is that short alfalfa plants have higher proportion of stems over leaves than tall alfalfa and fescue, and cows can produce bite sounds with lower amplitude, increasing confusion between events. Consequently, sound recordings for short forages, particularly alfalfa, may have a lower signal-to-noise ratio that can introduce errors in the classification of events. In the same way as for the first database good results for the classification of chews were obtained, which is a good sign for identification of rumination activities. Moreover, some degree of confusion between bites and chew-bites was also observed. That could be ameliorated by incorporating new sound features like a measure of symmetry of the event or information about the sequence of events.

Finally, as shown in the flowchart of the algorithm (Figure 3), any detected event that is not classified as chew-bite, bite or chew, is treated as noise event. However, potential insertions (false positive event) can occur when a given noise event is indeed misclassified as false chew, bite or chew-bite. To assess the odds for misclassified insertions, all likely insertions (false positive events due to noise) performed by CBRTA were further examined

593 with the HTK performance tool. **This analysis showed a low number**
594 **of insertions, which has two plausible explanations.** First, acoustic
595 monitoring was conducted with directional microphones (sensing only in one
596 direction) facing inward onto the forehead of cows and covered by a rubber
597 foam (Milone et al., 2009). Furthermore, this instrumentation was made
598 to minimize environmental noise (i.e. wind) to avoid the use of stronger
599 high-pass filters, that otherwise will remove important information of sound
600 signals. Second, the use of a low-pass filter with cutoff frequency of 5.5 Hz
601 (or 3.5 Hz depending of database) for computing envelope was preferred over
602 other filtering options. Noise is generally characterized as a non-stationary
603 signal with high energy at high frequencies, and it would be expected that any
604 noise energy that matches the frequency band of interest will have minimal
605 influence or interference on both, detection and classification tasks.

606 6. Conclusions

607 It has been demonstrated the importance of acoustic monitoring for both
608 detection and classification of ingestive events in grazing ruminants. Al-
609 though this technique is very appropriate, it presents difficulties to automat-
610 ically analyze large volume of high-quality audio signals by means of fast
611 methods. These difficulties are usually related to computation load, power
612 supply, data transfer and storage capacity. In this regard, the proposal was
613 to develop an alternative algorithm that can get high accuracy for detection
614 and classification, but with minimal computational cost.

615 The novel CBRTA algorithm was capable to combine very low computa-
616 tional cost with high accuracy for detection (up to 97.4%) and classification

617 (up to 84.0%) of chews, bites and chew-bites in grazing dairy cattle. Fur-
618 thermore, the linear computational complexity of CBRTA combined with
619 the use of low sampling frequency and quantization level further minimized
620 computational costs, which is a remarkable achievement in acoustics because
621 it can lend to the application of very fast real-time execution for timely and
622 accurate monitoring devices of grazing behavior. To the best of our knowl-
623 edge, there are no other acoustic platforms that can be used for real-time
624 analysis of sound signals in low cost embedded systems mounted on individ-
625 ual animals. The testing of CBRTA shows that with a sampling frequency of
626 4 kHz, good overall performance rate can be obtained at low computational
627 cost. This suggests that the main energy for classification of ingestive events
628 would be below to 2 kHz in a target signal, consistent with previous results
629 obtained by Milone et al. (2012).

630 Given the demonstrated applicability of acoustic signals to assess herbage
631 intake (Laca et al., 2000; Galli et al., 2011), future research steps must be
632 focused on the automation of herbage intake measurements, as well as, on
633 the application of acoustic monitoring as novel precision grazing manage-
634 ment tool. Future equipment development must also focus on both integral
635 applications that allow temporary storage or easy transfer of processed re-
636 sults via wireless network, and on intelligent power supply systems, that can
637 assure long-time operation of acoustic devices and embedded microproces-
638 sors in field applications. The CBRTA algorithm has promising capability to
639 facilitate these requirements.

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652 Appendix A. CBRTA complexity analysis

653 This appendix evaluates the computational cost of each step of the CBRTA
654 algorithm, which depends on the number of samples n to be processed per
655 second ($f_{CBRTA}(n)$). For this algorithm, the number of samples n to be pro-
656 cessed per second depends on the sampling frequency. Hence, the number of
657 operations required by each stage of the algorithm will depend on the task
658 being performed:

- 659 1. **Signal rectification:** A simple pre-processing task that guarantee a
660 positive sign for all samples. This task requires only a comparison and
661 a multiplication ($2n$ operations/s).
- 662 2. **Signal filtering:** A second-order low pass filter is applied to the result-
663 ing signal to obtain the sound envelope. This filter can be implemented

664 in two different ways: i) A second order **infinite impulse response**
665 **(IIR) filter** that involves five multiplications and four additions ($9n$
666 operations/s) or ii) a finite impulse response (FIR) filter that involves
667 P multiplications and P additions ($2Pn$ operations/s), where P is the
668 number of taps employed by the filter. The use of one particular way of
669 implementing the filter will depend on the main constraint of the imple-
670 mentation, such as computational efficiency for the FIR or numerical
671 stability for the IIR.

672 3. **Signal subsampling:** To reduce the computational requirements (load
673 and time) in the subsequent tasks, without losing accuracy, the sound
674 envelope is subsampled from its original sampling frequency of 100 Hz.
675 This task requires an addition and a comparison ($2n$ operations/s).

676 4. **Samples buffering:** The data stream generated in previous tasks is
677 divided into short segments. From a computational point of view this
678 task only involves counting of samples, which requires an addition (100
679 operations/s).

680 5. **Threshold generation:** The time-varying threshold $T(k)$ is computed
681 through two steps: the computation of the peak expectation threshold
682 (T_P), which requires five additions and one multiplication (600 oper-
683 ations/s), and the computation of the threshold $T(k)$, which requires
684 one addition and two comparisons (300 operations/s). Therefore, the
685 overall computational complexity of this task is 900 operations/s.

686 6. **Event detection:** This task only involves the comparison of the thresh-
687 old $T(k)$ with the sound envelope, which implies a computational com-
688 plexity of 100 operations/s.

- 689 **7. Properties computation:** This task computes the properties of the
690 sound envelope for classification of events. The shape of a given event
691 is quantified through computation of the number of changes in the
692 sign of the envelope slope when its magnitude is bigger than the back-
693 ground noise. It requires one comparison and one subtraction (200
694 operations/s). The duration of the event is computed from the sound
695 envelope by counting the number of samples when the envelope is big-
696 ger than the background noise. It requires one comparison and one
697 addition (200 operations/s). Finally, the maximum amplitude of the
698 event is computed directly from the absolute value of sound over a win-
699 dow of time whose length is half of the duration of a typical chew-bite
700 event. It only requires one comparison (100 operations/s).
- 701 **8. Event classification:** Using a set of five rules, based on the proper-
702 ties computed in the previous stage, the events are classified into chew,
703 bite, chew-bite, silence and noise. The evaluation of a rule to clas-
704 sify a silence only requires the comparison of the sample counter k_T ,
705 which involve 100 operations/s. To evaluate the remaining rules, the
706 algorithm checks the conditions that define each type of event. There-
707 fore, the overall computational complexity for each of these rules is 500
708 operations/s. Since all rules are evaluated at every event, the overall
709 complexity for this task is 2100 operations/s.

710 A linear complexity for CBRTA is given by the total number of opera-
711 tions per second that are required to be executed for an IIR low-pass filter
712 implementation, as follows:

$$f_{CBRTA}(n) = 13n + 3700. \quad (\text{A.1})$$

713 **Appendix B. CBHMM complexity analysis**

714 The cost of each step of the CBHMM algorithm presented by Milone et al.
 715 (2012) is evaluated as a function of the number of samples n to be analyzed
 716 per second ($f_{CBHMM}(n)$), where n depends on the sampling frequency. The
 717 corresponding system was implemented by the authors using the HTK toolkit
 718 (Young et al., 1997).

719 The signal will be analyzed using overlapped windows. Window duration
 720 w_L and window step w_S were defined as 60 ms and 40 ms, respectively.
 721 Regardless of the sampling frequency of input audio the number of windows
 722 n_w to be processed per second is

$$n_w = \left\lfloor \frac{s_L - w_L}{w_S} \right\rfloor + 1 = \left\lfloor \frac{1000 \text{ ms} - 60 \text{ ms}}{40 \text{ ms}} \right\rfloor + 1 = 24 \text{ windows} \quad (\text{B.1})$$

723
 724 where s_L is the duration of the segment of signal to analyze. The number of
 725 samples n_S to be processed per window depends on the number of samples
 726 to be analyzed as

$$n_S = \frac{w_L}{s_L} n. \quad (\text{B.2})$$

727 Recognition processes can be separated into two main stages: i) feature
 728 extraction and ii) classification. During the feature extraction stage, each
 729 window is analyzed with the same exact processes. The following complexity
 730 analysis will be done for a single window of n_S samples:

- 731 1. **Pre-emphasis filter**: a simple pre-processing operation emphasizes
732 the signal by applying a first order difference equation, that involves
733 an addition and a multiplication ($2n_S$ operations).
- 734 2. **Windowing**: a Hamming window function is applied to pre-processed
735 signal. This operation requires a multiplication for each sample of the
736 window (n_S operations).
- 737 3. **Window energy**: is a numeric value obtained from windowed signal
738 that will be part of the feature vector. It requires $2n_S$ operations.
- 739 4. **Fourier transform**: the windowed signal is transformed using a fast
740 Fourier transform, and magnitude is then taken. Complexity of these
741 computations are $n_S \log(n_S)$ and n_S operations, respectively.
- 742 5. **Filterbank analysis**: is a simple transform based on a bank of tri-
743 angular filters designed to give approximately equal resolution on a
744 mel-scale. Each Fourier magnitude coefficient is multiplied by the cor-
745 responding filter gain and the results are then accumulated. Thus,
746 each bin holds a weighted sum representing the spectral magnitude in
747 that filterbank channel. Ten filters that spread between 0 and 500 Hz
748 were selected by Milone et al. (2012). The complexity is a function
749 of the maximum length of the filter F_{ML} , it is at most $20F_{ML}$ opera-
750 tions. Because it is clear that $F_{ML} \ll n_S$, then this operation should
751 not be the most computationally expensive. It could be established a
752 computational complexity of $20n_S$ operations as upper bound.
- 753 6. **Logarithm**: is applied to each channel parameter of the filterbank.
754 This requires 10 operations (10 operations).
- 755 7. **Deltas**: a feature vector is composed by 22 elements is arranged by

756 10 log-filterbank parameters, window energy, deltas of log-filterbank
757 parameters, and delta of energy. Deltas computation requires 11 addi-
758 tional operations.

759 The total number of operations required to extract features $f_{fe}(n_S)$ from
760 a single window is

$$f_{fe}(n_S) = 21 + 26 n_S + n_S \log(n_S). \quad (\text{B.3})$$

761 This number must be multiplied by n_w to obtain the complete number of
762 operations in the feature extraction stage for one second of audio. The cost
763 of classification stage is revised below under the same assumption that one
764 second of audio must be processed.

765 Given the small number of models in this application (only 3: chew, bite
766 and chewbite, without taking into account the silence model for simplicity)
767 it is reasonable to suppose a similar complexity than in an isolated word
768 recognition task. Also, one second of audio could contain only one event,
769 due to the typical duration of masticatory events. Thus, to do isolated word
770 recognition, the following steps must be performed: (i) generate a sequence of
771 feature vectors corresponding to the audio, (ii) calculate the model likelihoods
772 for all possible models, and, (iii) select the word whose model likelihood is
773 highest.

774 Step (i) was already addressed in feature extraction stage. To perform
775 step (ii) the Viterbi algorithm is used. This algorithm requires on the order
776 of VQ^2T computations, where V is the number of words, Q is the number of
777 states in each model, and T is the length of the feature vectors sequence (Ra-
778 biner and Juang, 1993). Since $V = 3$ (chew, bite and chewbite), $Q = 4$ and

779 $T = 24.5$ (number of windows per second), the viterbi computations needed
 780 are $VQ^2T = 1,176$. Each Viterbi computation requires one multiplication,
 781 one addition, and a likelihood calculation (at least $M(d + d^2)$ operations
 782 (Duda, Hart, pp. 111), where $d = 22$ is the number of features, and the
 783 number of mixed gaussians is $M = 90$). Then, the operations needed in step
 784 (ii) are $VQ^2T(2 + M(d + d^2)) = 53,557,392$. Operations performed in step
 785 (iii) are just 3 comparisons to obtain the highest likelihood. Therefore, the
 786 number of operations performed in classification stage is determined by step
 787 (ii).

788 The algorithm CBHMM shows a superlinear complexity where the total
 789 number of operations per second of signal required to execute this algorithm
 790 is the sum of feature extraction and classification stage costs, as follows:

$$f_{CBHMM}(n) = 24 \left\{ 21 + 26 \frac{w_L}{s_L} n + \frac{w_L}{s_L} n \log \left(\frac{w_L}{s_L} n \right) \right\} + 53,557,392. \quad (\text{B.4})$$

791 **References**

- 792 Alkon, P. U., Cohen, A., 1986. Acoustical biotelemetry for wildlife research:
793 a preliminary test and prospects. *Wildlife Society Bulletin* 14 (2), 193–196.
- 794 Alkon, P. U., Cohen, Y., Jordan, P. A., 1989. Towards an acoustic bioteleme-
795 try system for animal behavior studies. *The Journal of Wildlife Manage-*
796 *ment* 53 (3), 658–662.
- 797 Christov, I. I., 2004. Real time electrocardiogram QRS detection using com-
798 bined adaptive threshold. *BioMedical Engineering OnLine* 3 (1), 28–37.
- 799 Clapham, W. M., Fedders, J. M., Beeman, K., Neel, J. P., 2011. Acoustic
800 monitoring system to quantify ingestive behavior of free-grazing cattle.
801 *Computers and Electronics in Agriculture* 76 (1), 96–104.
- 802 De Boever, J., Andries, J., De Brabander, D., Cottyn, B., Buysse, F., 1990.
803 Chewing activity of ruminants as a measure of physical structure—a review
804 of factors affecting it. *Animal Feed Science and Technology* 27 (4), 281–291.
- 805 Delagarde, R., Caudal, J.-P., Peyraud, J.-L., 1999. Development of an auto-
806 matic bitemeter for grazing cattle. *Annales de Zootechnie* 48 (5), 329–339.
- 807 Duda, R. O., Hart, P. E., Stork, D. G., 2001. *Pattern classification*, second
808 ed. John Wiley and Sons.
- 809 Duizer, L., 2001. A review of acoustic research for studying the sensory per-
810 ception of crisp, crunchy and crackly textures. *Trends in Food Science &*
811 *Technology* 12 (1), 17–24.

- 812 Galli, J. R., Cangiano, C. A., Demment, M., Laca, E. A., 2006. Acoustic
813 monitoring of chewing and intake of fresh and dry forages in steers. *Animal*
814 *Feed Science and Technology* 128 (1), 14–30.
- 815 Galli, J. R., Cangiano, C. A., Milone, D. H., Laca, E. A., 2011. Acoustic
816 monitoring of short-term ingestive behavior and intake in grazing sheep.
817 *Livestock Science* 140 (1), 32–41.
- 818 Hodgson, J., Illius, A. W., et al., 1996. *The Ecology and Management of*
819 *Grazing Systems*. CAB international, England.
- 820 Laca, E., Ungar, E., Seligman, N., Ramey, M., Demment, M., 1992. An in-
821 tegrated methodology for studying short-term grazing behaviour of cattle.
822 *Grass and Forage Science* 47 (1), 81–90.
- 823 Laca, E., WallisDeVries, M., et al., 2000. Acoustic measurement of intake
824 and grazing behaviour of cattle. *Grass and Forage Science* 55 (2), 97–104.
- 825 Milone, D., Rufiner, H., Galli, J., Laca, E., Cangiano, C., 2009. Computa-
826 tional method for segmentation and classification of ingestive sounds in
827 sheep. *Computers and Electronics in Agriculture* 65 (2), 228–237.
- 828 Milone, D. H., Galli, J. R., Cangiano, C. A., Rufiner, H. L., Laca, E. A.,
829 2012. Automatic recognition of ingestive sounds of cattle based on hidden
830 Markov models. *Computers and Electronics in Agriculture* 87 (1), 51–55.
- 831 Navon, S., Mizrach, A., Hetzroni, A., Ungar, E. D., 2013. Automatic recog-
832 nition of jaw movements in free-ranging cattle, goats and sheep, using
833 acoustic monitoring. *Biosystems Engineering* 114 (4), 474–483.

- 834 Rabiner, L., Juang, B.-H., 1993. Fundamentals of speech recognition.
835 Prentice-Hall.
- 836 Sauvant, D., 2000. Granulométrie des rations et nutrition du ruminant. Pro-
837 duction Animales-Paris-Institut National de la Recherche Agronomique
838 13 (2), 99–108.
- 839 Tani, Y., Yokota, Y., Yayota, M., Ohtani, S., 2013. Automatic recognition
840 and classification of cattle chewing activity by an acoustic monitoring
841 method with a single-axis acceleration sensor. Computers and Electron-
842 ics in Agriculture 92 (1), 54–65.
- 843 Ungar, E. D., Rutter, S. M., 2006. Classifying cattle jaw movements: com-
844 paring IGER behaviour recorder and acoustic techniques. Applied Animal
845 Behaviour Science 98 (1), 11–27.
- 846 Watt, L., Clark, C., Krebs, G., Petzel, C., Nielsen, S., Utsumi, S., 2015. Dif-
847 ferential rumination, intake, and enteric methane production of dairy cows
848 in a pasture-based automatic milking system. Journal of Dairy Science
849 98 (10), 7248–7263.
- 850 Young, S., Evermann, G., Gales, M., Hain, T., Kershaw, D., Liu, X., Moore,
851 G., Odell, J., Ollason, D., Povey, D., et al., 1997. The HTK book. Vol. 2.
852 Entropic Cambridge Research Laboratory Cambridge.