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. Perfor-
mance 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 environ-
ment ($N = 50$). 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 de-
tect 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 mem-
ory. 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 **1. Introduction**

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

grazing animals (Hodgson et al., 1996; Delagarde et al., 1999). One possible and reliable way is through the detection of distinct jaw movements associated with three common basic events: bites, chews and compound chew-bites (Milone et al., 2012). A grazing bite includes the apprehension and severance of herbage, while a grazing or rumination chew includes the crushing, grinding and processing of consumed herbage. The chew-bite is a third important grazing event that results from the overlapping of chewing and biting on a same jaw movement. Thus, jaw movements can serve as a reliable measure of distinct grazing and rumination cycles. Furthermore, the quantification of rumination chews could provide rich information on the ruminal fermentation of fiber and correlated changes in rumen pH (Sauvant, 2000). Likewise, herbage intake rate appears to depend on trade-offs between ingestive bites, chews and chew-bites, and the monitoring of these events could therefore inform on the ability of grazing herbivores to modulate changes in intake rate (Laca et al., 2000). While the number and characteristics of grazing and rumination events vary according to several plant, animal and environmental factors, they could be monitored as indicators of animal health, welfare or nutritional status (De Boever et al., 1990). To the best of our knowledge, only few studies have been focused on developing automated systems to monitoring changes in grazing and rumination.

One plausible approach to measure feeding behavior is acoustic monitoring. Alkon and Cohen (1986) and Alkon et al. (1989) used acoustic biotelemetry to study the feeding behavior of porcupine. Laca et al. (1992) instrumented an inward-facing microphone on the forehead of steers to register stronger and readily distinguishable sounds of bites, chews and chew-bites.

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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

4

calibration before it can be used with different animals, pastures or exper-

imental conditions. The capacity of the recording device and power source

were among other limitations of the proposed system.

Navon et al. (2013) implemented an algorithm that used a machine-

learning approach to analyze time-domain features (i.e., shape, intensity,

duration and sequence of events) of ingestive sounds in grazing cattle. The

procedure eliminated the need of calibrations and allowed a detection of in-

gestive events with a 94% correct and 7% false identification. More recently,

Tani et al. (2013) applied pattern recognition techniques to iteratively mea-

sure eating and ruminating events collected by a single-axis accelerometer.

The recognition patterns were defined in frequency domain and used to iden-

tify and classify likely eating and rumination events. Without previous cal-

ibration, recognition results were similar to previous analytical procedures

used by Clapham et al. (2011) and Navon et al. (2013) . However, likely lim-

itations of the methodology were associated with the spectral similarities be-

tween rumination and eating signals, presence of non-stationary background

noise, and high computational cost associated with the analysis of signals

sampled at high frequency.

Although several of the previous instrumentation and analytical proce-

dures have shown good performance for detection of signals associated with

eating and/or rumination, few of them offered possibilities to accurately clas-

sify exclusive bites, chews and chew-bites, which is a necessary condition for

reliable measures of grazing behavior and even for estimation of herbage in-

take by means of acoustic methods. Furthermore, most if not all of previous

methodologies deal with high quality and long duration signals (hours or

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

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

2. The algorithm

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

106 time-domain instead of transformed-domain (frequency, time-frequency) anal-

107 ysis was implemented to avoid high computational load of signal analysis.

108 *2.1. General description*

109 Signals associated with an exclusive chew (Figure 1a), composite chew-

110 bite (Figure 1b) or exclusive bite (Figure 1c) have readily distinguishable
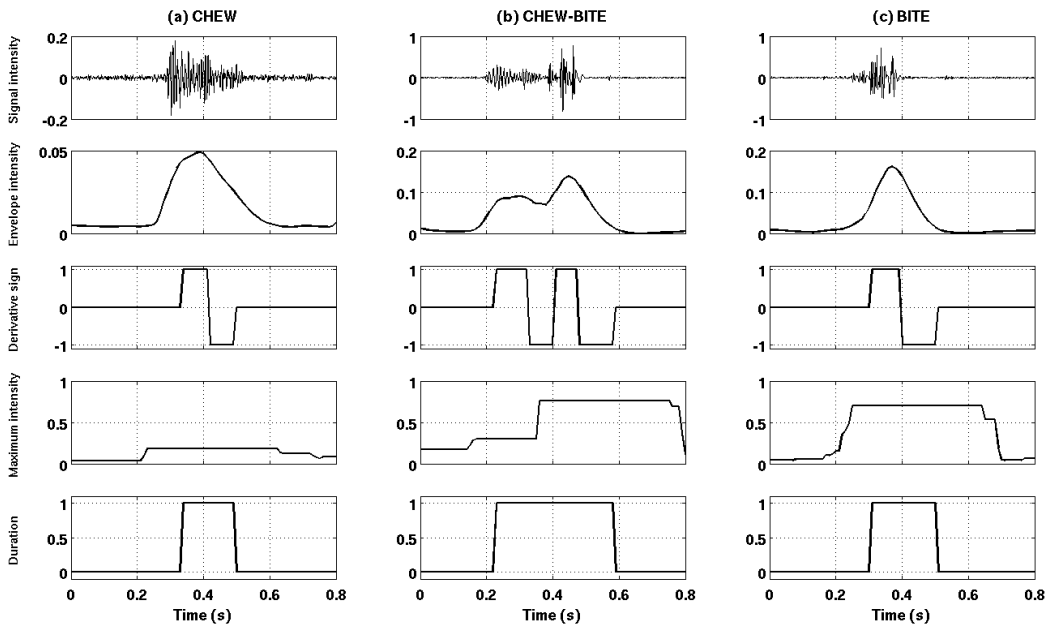
111 properties.

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.

112 Therefore, the shape, maximum intensity and duration of sounds were

113 isolated to discriminate among the bites, chews and chew-bites. The shape

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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

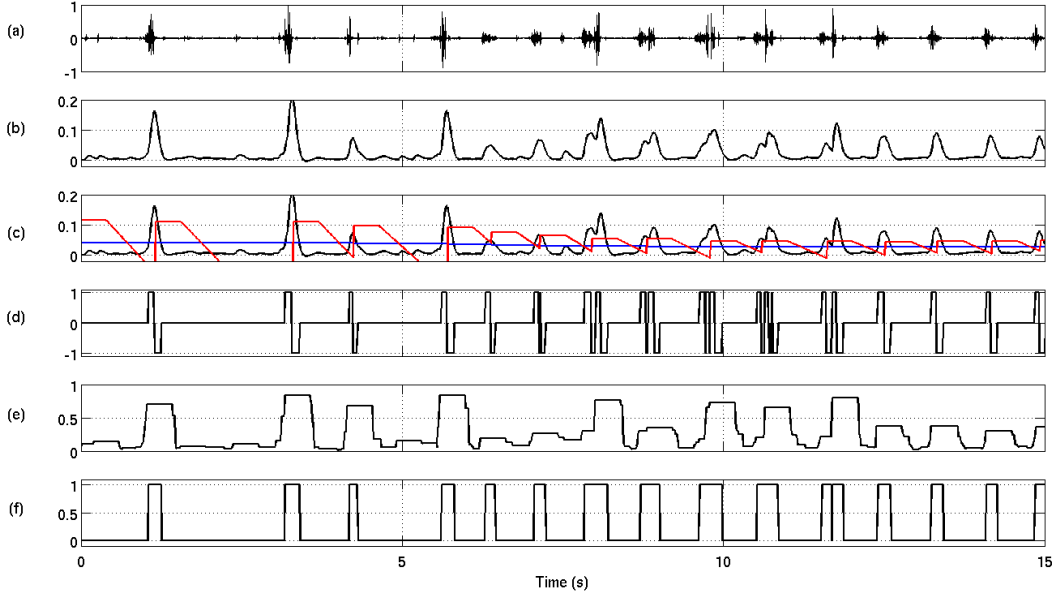138 subsampling. In the first step the absolute value of signal samples is com-

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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.

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

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

9

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.

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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

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

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

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

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).

11

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

12

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** $NC <= 2$ **and** $EA >= 0.5\ T_P$ **and** $ED < 0.3[s]$ **then** $L(j)$=B
Chew	**if** $NC <= 2\ EA > NT$ **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
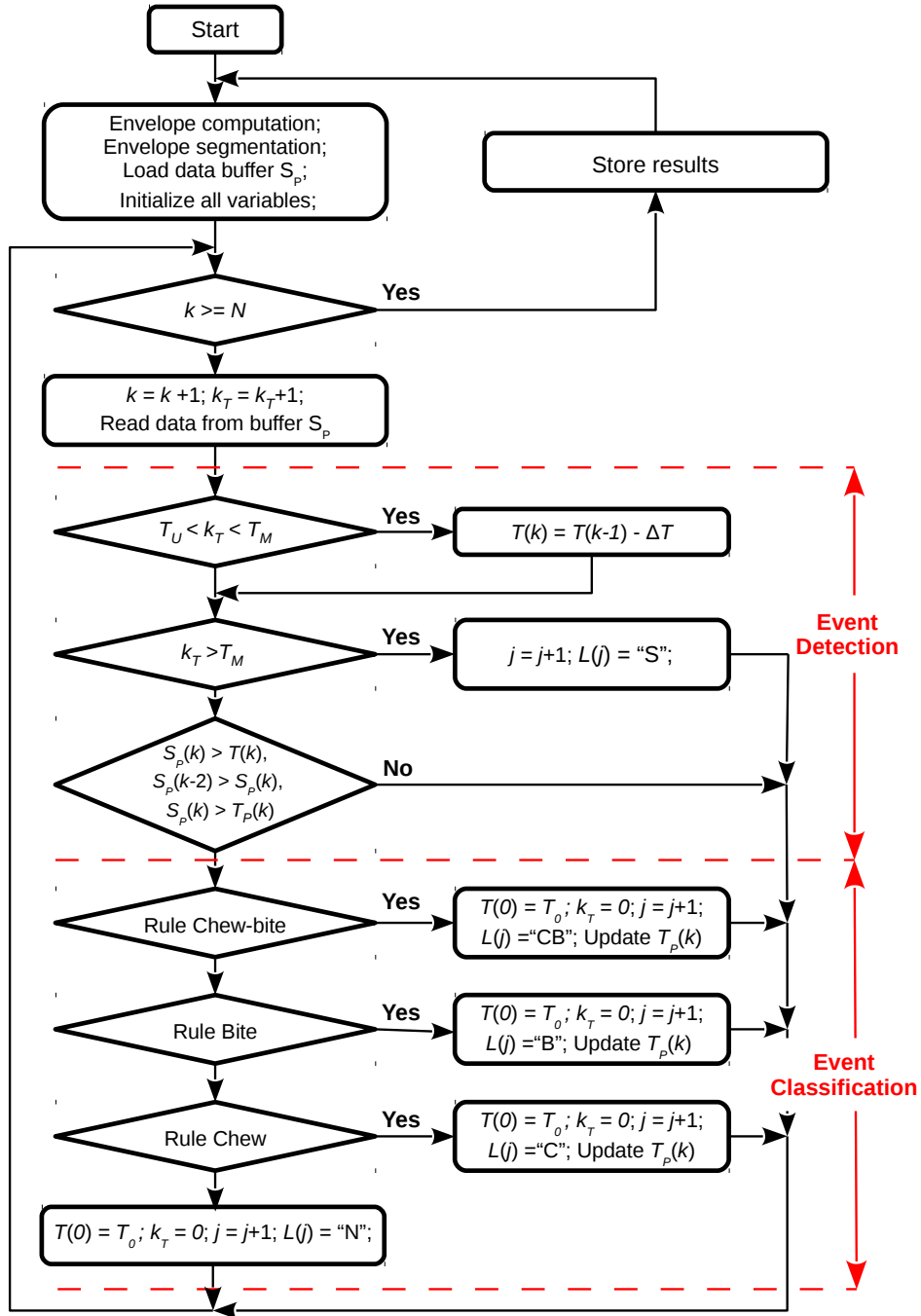
Figure 3: Flow diagram of the algorithm for event detection and classification.

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

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

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

16

signals contained approximately 13 min of recording and around 800 events

(13% bites, 64% chews and 23% chew-bites). Hereafter, these recordings will

be referred as the Rosario Database (RDb).

All signals were labeled aurally by experts in animal behavior to identify

and classify individual events (C, B, CB, S, N) during grazing. The labeling

process was done by one expert, and the result was checked by another

expert. In most of the cases experts largely agreed with the labeling of

signals, but when there was disagreement, both experts worked together

to provide a final decision. This labeling was used as control reference for

comparison and testing of the performance of the algorithm. In the case

of signals belonging to MDb, two periods of 5 minutes were extracted and

labeled from each 24h sound track. The signals were randomly selected

within a grazing period, because during this activity the three types of events

considered can be found. Each period contained approximately 350 events

(25% bites, 48% chews and 27% chew-bites). One of the periods was used to

analyze the effect of parameters while the other one was used for evaluation

purposes. A similar data partition was made for signals belonging to RDb.

For each grazing session, 50% of signals were used to analyze the effect of

parameters, while the remaining 50% was used for evaluation purposes.

3.2. Performance measures

Valid comparisons between events recognized and classified by the algorithm and their corresponding reference of aurally labeled events depends on the correct synchronization of both event sequences. To solve this problem, the HTK[1] performance analysis tool HResults was used, which is based on a dynamic programming-based string alignment procedure (Young et al.,

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³⁰⁹ 1997).

³¹⁰ The outputs of this tool were: i) the number of deleted events (D), which
³¹¹ are false negatives, ii) the number of substituted events (S), which are mis-
³¹² classified events, iii) the number of inserted events (I), which are false pos-
³¹³ itives, and iv) the total number of events (T) in the reference transcription
³¹⁴ provided by the experts. An example of these definitions is shown in Table 2:
³¹⁵ the first bite of the recognized sequence is a substitution (S) because the real
³¹⁶ event is a chew; the second chewbite is an insertion (I) because there is no
³¹⁷ event in the real sequence; and the second chew in the reference sequence
³¹⁸ has not been recognized so it is a deletion (D).

Table 2: Example of sequence alignment for performance measurement.

Reference seq.:	chewbite	chew	chew	bite	chew		bite	bite
Recognized seq.:	chewbite	bite		bite	chew	chewbite	bite	bite

³¹⁹ Keeping these definitions in mind, the percentage of detected events is
³²⁰ computed as follows[2]

$$\delta\% = \frac{T - D}{T}\ 100\%, \tag{3}$$

³²¹

³²² the percentage number of events correctly recognized is given by

$$C\% = \frac{T - D - S}{T}\ 100\%, \tag{4}$$

³²³

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[2]http://htk.eng.cam.ac.uk/

18

sinc(i) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
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324 and the accuracy is computed by

$$A\% = \frac{T - D - S - I}{T} \; 100\%. \tag{5}$$

325 Performance of CBRTA for recognition of C, B, CB, S or N was assessed
326 using exploratory analysis of sensitivity. This analysis computed the cor-
327 respondent recognition rate $C\%$, accuracy $A\%$ and computational time as
328 a function of changes in the following key parameters: i) the sampling fre-
329 quency, ii) quantization level, iii) cut-off frequency of the detector filter, and
330 iv) subsampling frequency. The effectiveness of CBRTA for detection of in-
331 gestive events (C, B, CB) was determined considering false negatives in the
332 computation, but no substitutions[3]. The effectiveness of CBRTA for clas-
333 sification of ingestive events (C, B, CB) was determined in two ways. For
334 the MDb database, a cross-way validation was conducted in order to demon-
335 strate robustness. For this comparison, the CBRTA was fitted with the best
336 set of parameters for the MDb and RDb database, respectively. By best set
337 of parameters we means a set of parameters that provides the highest recog-
338 nition rate with the highest accuracy. Then, the classification by CBRTA
339 fitted with the best set of parameters for MDb database [CBRTA (MDb)]
340 was compared to the correspondent classification of CBRTA fitted with the
341 best set parameters for the RDb database [CBRTA (RDb)]. For the RDb
342 database, the CBRTA was compared to the CBHMM algorithm of Milone
343 et al. (2012). This comparison was decided for two reasons. The CBHMM

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

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is the only other available method that makes a distinct classification of C,
B and CB, and, the CBRTA and CBHMM are both originally fitted to the
same RDb database, thus offering a direct unbiased comparison of methods.
On the other hand, the application of the CBHMM method on a different
database could be wrong, because the models would need to be adapted to
the new recording conditions. Also, it is important to note that to train and
evaluate the CBHMM, a hold-out cross-validation method was used (Duda
et al., 2001), while in the present CBRTA parameterization is done using a
subset of RDb data not further used for testing purposes. The CBRTA was
implemented using MATLAB R2010b for evaluation purposes.

Thereafter, the analysis included the testing of i) algorithm complexity,
ii) computational performance, and iii) validation of CBRTA for both the
automatic detection and classification of ingestive events in grazing dairy
cattle. The computational complexity was modeled for each computational
task as the function of the number of samples n to be processed each sec-
ond. For more exhaustive analysis, the computational cost of CBRTA was
compared to the CBHMM algorithm proposed by Milone et al. (2012).

4. Results

4.1. Complexity analysis

The computational cost for each step of the CBRTA algorithm evalu-
ated as function of the number of samples n to be processed each second

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[3]This 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.

20

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

4.2. Effect of parameters on system performance

Figure 4 shows the effect of sampling frequency on the performance of the algorithm (recognition rate and accuracy) and the corresponding computational time for the MDb database. The recognition rate and accuracy remained high (around 80%) over wide range of frequencies (from 2 kHz to 11 kHz) and declined for frequencies that were outside of this range. This phenomenon can be explained by the fact that for sampling frequencies below 2 kHz the signal/noise ratio is degraded because important components

21

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

of the signal are filtered out. In a similar way, once the sampling frequency goes beyond 11 kHz, the amount of noise processed by the algorithm increases, further reducing and degrading the overall signal/noise relationship. However, in the range of frequencies from 2 kHz to 11 kHz, the information and noise processed by the algorithm remains unchanged, keeping the overall signal/noise relationship constant.
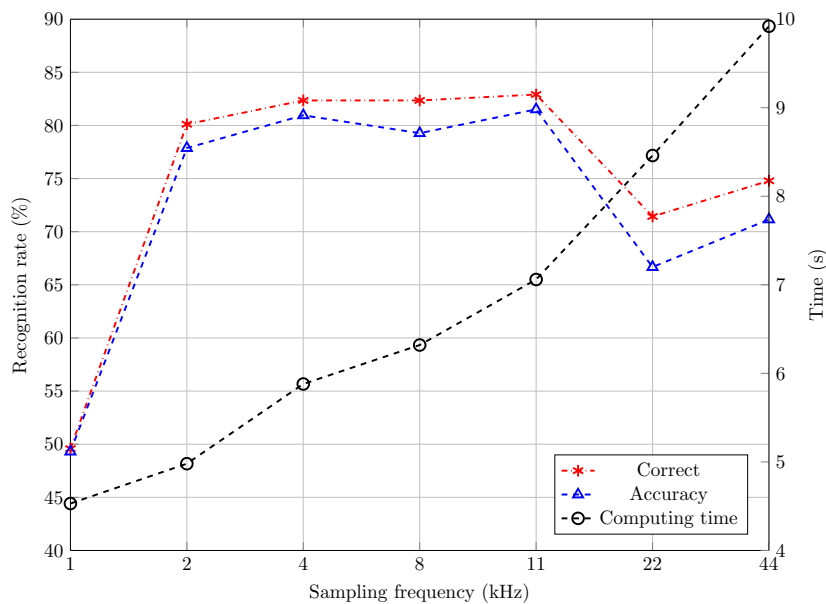

Figure 4: Algorithm recognition rate and accuracy and corresponding computational time as a function of sampling frequency for frames of 5-minute duration (N=25).

The linear dependency of the computational time with sampling frequency 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

⁴⁰² application the algorithm is capable to analyze 50 minutes of acoustic data

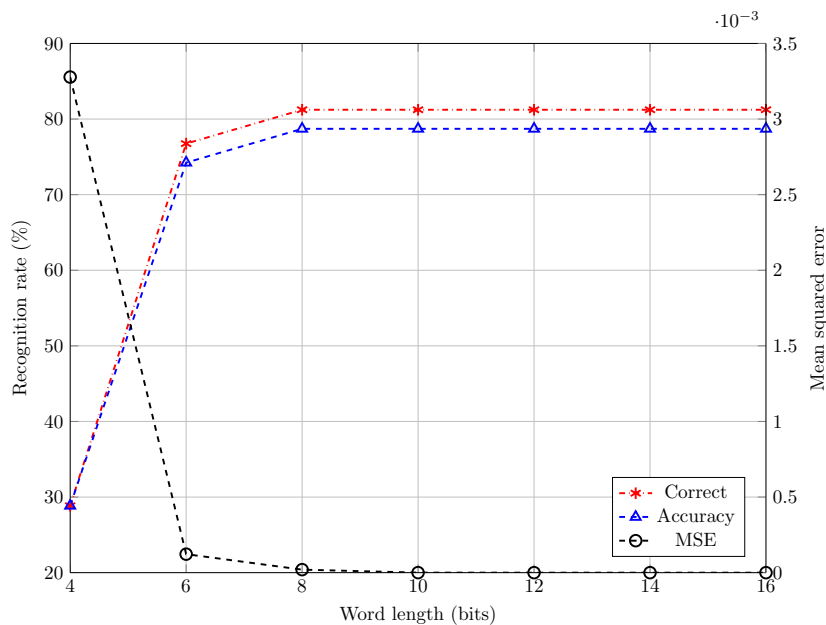⁴⁰³ per minute in a standard desktop computer.

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

⁴⁰⁴   Figure 5 shows the effect of quantization level (or word length represen-

⁴⁰⁵ tation) on the performance of the algorithm (recognition rate and accuracy)

⁴⁰⁶ for the MDb database. The recognition rate and accuracy remained high

⁴⁰⁷ (around 80%) for a quantization level of 8 bits or more. This phenomenon

⁴⁰⁸ can be explained by the fact that the quantization error, measured in terms

⁴⁰⁹ of the mean square error (MSE) between the signal represented by data of

⁴¹⁰ a given word length (resolution) and the signal represented by data of the

⁴¹¹ longest word (16 bits), is almost zero for ingestive sound data codified with
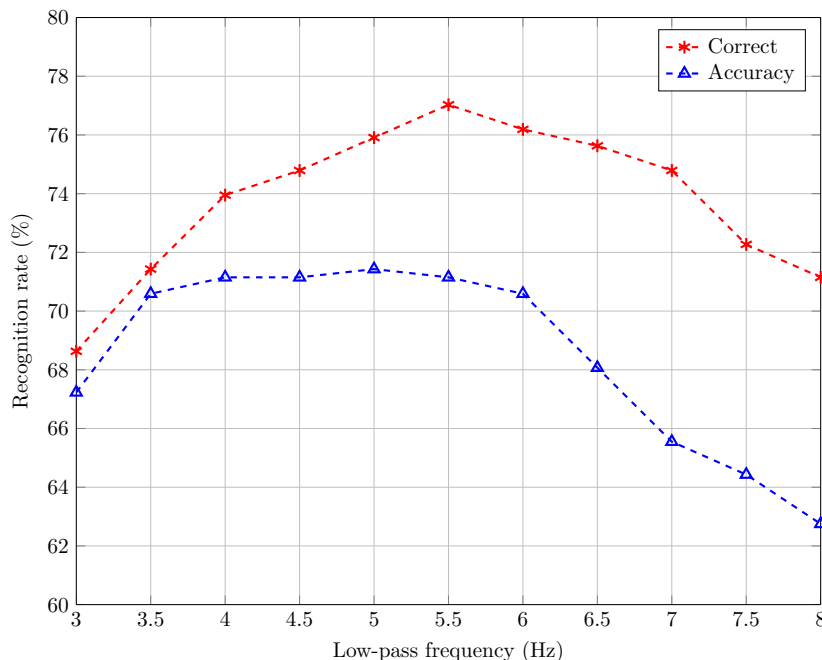
24

⁴¹² 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).

⁴¹³ Figure 6 shows the effect of the cut-off frequency of the envelope detector
⁴¹⁴ filter on the recognition rate and accuracy for the MDb database. Both,
⁴¹⁵ recognition rate and accuracy improved as the cut-off frequency of the fil-
⁴¹⁶ ter increased from 3 Hz to 5 Hz. A correct recognition rate over 75% and
⁴¹⁷ accuracy over 70% was observed in the frequency range between 5 Hz and
⁴¹⁸ 6 Hz. Beyond 6 Hz, both recognition and accuracy declined. These phe-
⁴¹⁹ nomena can be explained by the fact that enlarging the bandwidth of the
⁴²⁰ filter at low frequencies increases the amount of information processed by
⁴²¹ the algorithm, thereby augmenting the overall signal/noise relationship and

25

the performance of the algorithm. However, once the cut-off frequency goes

beyond the 6 Hz, the information remains constant, the amount of noise pro-

cessed by the algorithm increases, and the overall signal/noise relationship
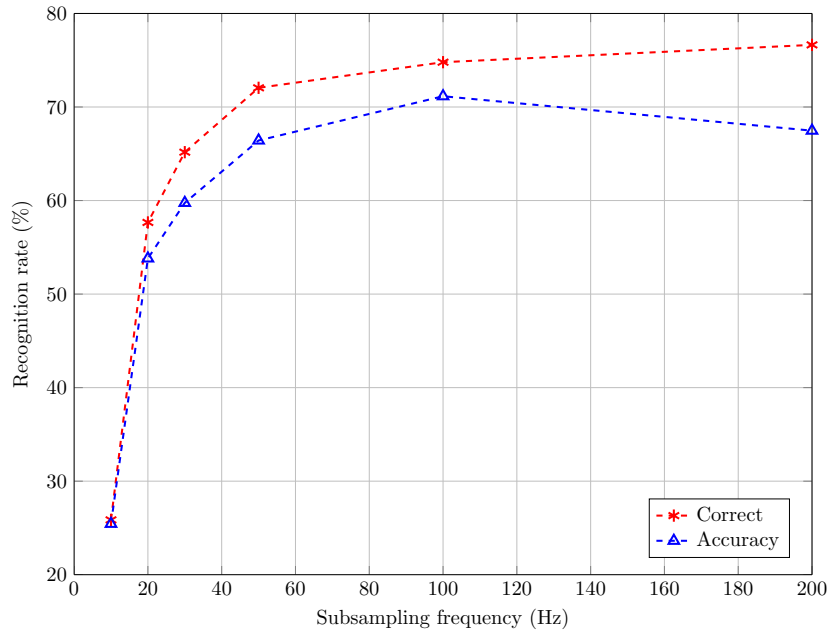
and performance of the algorithm decreases.

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

Figure 7 shows the effect of the subsampling frequency on the algorithm

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 fre-

quency the amount information processed by the algorithm increases, im-

proving the overall signal/noise relationship. However, once the subsampling

⁴³³ frequency goes beyond the 100 Hz, the useful information remains constant

⁴³⁴ and the overall signal/noise relationship does not suffer further change.

⁴³⁵ The algorithm performance analysis for the RDb database rendered a

⁴³⁶ slightly different trend (data not shown). Best recognition rate and accu-

⁴³⁷ racy was observed at sampling frequencies between 2 kHz and 4 kHz. With

⁴³⁸ respect to the filter cut-off frequency, the best results were observed at 3.5

⁴³⁹ Hz, where highest recognition with high accuracy was detected. Moreover,

⁴⁴⁰ similar recognition performance was obtained at cut-off frequencies of 4 Hz

⁴⁴¹ and 5 Hz, but with lowering accuracy. Regarding the subsampling frequency,

⁴⁴² the best performance was observed at 100 Hz, similarly to MDb database.

⁴⁴³ Also a sampling frequency of 2 kHz rendered lower overall computational

⁴⁴⁴ cost. The differences between the parameters of the algorithm obtained for

⁴⁴⁵ each database are primarily due to differences between the characteristics

⁴⁴⁶ (frequency response and steady state gain, among others) of microphones

⁴⁴⁷ used to record the databases.

⁴⁴⁸

⁴⁴⁹ *4.3. Event detection and classification*

⁴⁵⁰ As can be seen in Figure 3, when ingestive sounds are processed, two

⁴⁵¹ different task can be performed: i) detect the existence of an ingestive event

⁴⁵² within the record without identifying its type, and ii) classify the ingestive

⁴⁵³ event by identifying the type of event detected. Clearly, the detection task is

⁴⁵⁴ simpler and more accurate than the classification task, since it requires fewer

⁴⁵⁵ information.

⁴⁵⁶ For the algorithms considered in this paper the overall detection of in-

⁴⁵⁷ gestive events was 97.4%, because of the existence 2.6% of deletions (false

negatives). Also it was observed 1.4% of insertions (false positives). Regarding event classification, the CBRTA algorithm clearly distinguished among types of jaw movements in both MDb and RDb databases. In Table 4 the classification of ingestive events for the MDb is presented. The CBRTA algorithm shows an average recognition rate of 84.0% of the total events for CBRTA (MDb) and an average recognition rate of 79% of the total events for CBRTA (RDb). Therefore, the results for event classification were lower than event detection rate by an average of 15%. For both CBRTA (MDb) and CBRTA (RDb) sets of parameters the algorithm achieved good event classification rates, demonstrating ability for scalability and generalization. Also, Table 4 summarizes the recognition rates for each different event determined for the MDb database. In this table it can be observed the high ability of the algorithm to correctly identify the chew and bite events, regardless of the set of parameters used. However, some degree of confusion between bites and chew-bites was detected for the classification of chew-bites, which may be due to the close similarity of sound properties between both events. We believe that this confusion is less critical at a practical level since B and CB are both ingestive events.

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

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).

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 the algorithm can impose severe limitations for implementation in a system running in real-time, and this issue becomes relevant when high quality and long duration (several hours) audio need to be processed. For real-time operation, the algorithm must be able to process a given signal segment before another segment becomes available. To accomplish this objective, the algorithm must complete at least $f(n)$ fix-point operations per second. For the

29

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).

range of sampling rates considered in the CBRTA application (from 4 KHz to 44 Khz), it is easy to find a low cost commercial microprocessor capable to perform more than the required number of operations. For example, given a 44 Khz sample rate it is possible to complete the execution of CBRTA with a Tiva C microcontroller (Tiva$^{\text{TM}}$ C Series LaunchPad Evaluation Kit, Texas Instruments Inc., Dallas, TX) using a 10 MHz clock. The processing speed could be increased further (augmenting the clock frequency), but at the expense of increasing energy consumption, which is an essential issue in portable embedded systems.

In the present study we carried out a detailed analysis of computational complexity, performance of the CBRTA algorithm and the CBHMM algorithm to then have a comparative reference of computational complexities. This analysis showed a linear computational complexity for CBRTA algorithm ($O(n)$), while for the CBHMM method was found a greater superlinear complexity ($O(n \, log(n))$). In addition to showing a lower complexity, the CBRTA algorithm had proven capability of processing grazing signals 50 times faster than real-time. Others authors such as Clapham et al. (2011) have reached up to 10 times faster than real-time but for algorithms calibrated for detection of bites alone, excluding therefore two other critical jaw events in grazing animals, exclusive chews and compound chew-bites. Thus, fast processing by CBRTA is a promising result to develop embedded microcomputer applications that depend on real-time analysis.

Indeed, a major drawback to process signals real-time on embedded systems is the computational load of the algorithm, since this can determine the requirements of hardware to implement the system. In signal processing,

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

536 The overall performance of CBRTA on event detection was 97.4% across
537 the two databases, which is in the same order of detection rate for algorithms
538 published in the specialized literature. In this sense, Clapham et al. (2011)
539 reported a successful detection of bites of 95%, while Navon et al. (2013) re-
540 ported detection rates for jaw movements of 94% in a low noise environment.
541 Milone et al. (2012) developed an algorithm extending from HMM models to
542 detect and classify ingestive sounds of cattle (i.e. C, B and CB), reaching a
543 successful detection rate of 94%. In a similar way, Tani et al. (2013) detected
544 ingestive and ruminating chewing with approximately a 98% detection suc-
545 cess. These quantitative results (except the results of algorithm developed
546 by Milone et al. (2012) that used the same RDb database) are not directly

32

comparable to the present study because the studies vary in number and type of events analyzed, duration of records, type and height of pastures, recording procedures and devices, and validation methods. Furthermore, the data employed in those studies are not available for numerical experimentation. On the other hand, the remarkable capacity for event detection by CBRTA implies that further classification of ingestive events may not compromise the ability of an algorithm to efficiently detect ingestive events. Regarding the event classification stage, to assess the robustness of CBRTA, we decided to evaluate the performance of CBRTA for two sets of parameters, applied on the first database (MDb). The recognition rate averaged 84% when CBRTA was used with the best set of parameters for a partition (not further used for testing purposes) within the same database, and a performance rate of 79% when it was used with the best set of parameters for a partition (not further used for testing purposes) of a different database. This result shows that the algorithm seems to be robust to databases with large differences. For the second database (RDb), the proposed algorithm achieved a recognition rate of 77% on average, while the CBHMM method averaged 79.5% over all pastures. The best results achieved by CBHMM method is due 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

33

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 with the HTK performance tool. This analysis showed a low number of insertions, which has two plausible explanations. First, acoustic monitoring was conducted with directional microphones (sensing only in one direction) facing inward onto the forehead of cows and covered by a rubber foam (Milone et al., 2009). Furthermore, this instrumentation was made to minimize environmental noise (i.e. wind) to avoid the use of stronger high-pass filters, that otherwise will remove important information of sound signals. Second, the

34

use of a low-pass filter with cutoff frequency of 5.5 Hz (or 3.5 Hz depending of database) for computing envelope was preferred over other filtering options. Noise is generally characterized as a non-stationary signal with high energy at high frequencies, and it would be expected that any noise energy that matches the frequency band of interest will have minimal influence or interference on both, detection and classification tasks.

6. Conclusions

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

The novel CBRTA algorithm was capable to combine very low computational cost with high accuracy for detection (up to 97.4%) and classification (up to 84.0%) of chews, bites and chew-bites in grazing dairy cattle. Furthermore, the linear computational complexity of CBRTA combined with the use of low sampling frequency and quantization level further minimized computational costs, which is a remarkable achievement in acoustics because it can lend to the application of very fast real-time execution for timely and accurate monitoring devices of grazing behavior. To the best of our knowledge, there are no other acoustic platforms that can be used for real-time

⁶²¹ analysis of sound signals in low cost embedded systems mounted on individ-
⁶²² ual animals. The testing of CBRTA shows that with a sampling frequency of
⁶²³ 4 kHz, good overall performance rate can be obtained at low computational
⁶²⁴ cost. This suggests that the main energy for classification of ingestive events
⁶²⁵ would be below to 2 kHz in a target signal, consistent with previous results
⁶²⁶ obtained by Milone et al. (2012).

⁶²⁷ Given the demonstrated applicability of acoustic signals to assess herbage
⁶²⁸ intake (Laca et al., 2000; Galli et al., 2011), future research steps must be
⁶²⁹ focused on the automation of herbage intake measurements, as well as, on
⁶³⁰ the application of acoustic monitoring as novel precision grazing manage-
⁶³¹ ment tool. Future equipment development must also focus on both integral
⁶³² applications that allow temporary storage or easy transfer of processed re-
⁶³³ sults via wireless network, and on intelligent power supply systems, that can
⁶³⁴ assure long-time operation of acoustic devices and embedded microproces-
⁶³⁵ sors in field applications. The CBRTA algorithm has promising capability to
⁶³⁶ facilitate these requirements.

⁶³⁷ Acknowledgements

36

Appendix A. CBRTA complexity analysis

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

1. **Signal rectification**: A simple pre-processing task that guarantee a positive sign for all samples. This task requires only a comparison and a multiplication ($2n$ operations/s).

2. **Signal filtering**: A second-order low pass filter is applied to the resulting signal to obtain the sound envelope. This filter can be implemented in two different ways: i) A second order infinite impulse response (IIR) filter that involves five multiplications and four additions ($9n$ operations/s) or ii) a finite impulse response (FIR) filter that involves P multiplications and P additions ($2Pn$ operations/s), where P is the number of taps employed by the filter. The use of one particular way of implementing the filter will depend on the main constraint of the implementation, such as computational efficiency for the FIR or numerical stability for the IIR.

37

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

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

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

6. **Event detection**: This task only involves the comparison of the threshold $T(k)$ with the sound envelope, which implies a computational complexity of 100 operations/s.

7. **Properties computation**: This task computes the properties of the sound envelope for classification of events. The shape of a given event is quantified through computation of the number of changes in the sign of the envelope slope when its magnitude is bigger than the background noise. It requires one comparison and one subtraction (200 operations/s). The duration of the event is computed from the sound envelope by counting the number of samples when the envelope is bigger than the background noise. It requires one comparison and one

⁶⁹⁴ addition (200 operations/s). Finally, the maximum amplitude of the
⁶⁹⁵ event is computed directly from the absolute value of sound over a win-
⁶⁹⁶ dow of time whose length is half of the duration of a typical chew-bite
⁶⁹⁷ event. It only requires one comparison (100 operations/s).

⁶⁹⁸ 8. **Event classification**: Using a set of five rules, based on the proper-
⁶⁹⁹ ties computed in the previous stage, the events are classified into chew,
⁷⁰⁰ bite, chew-bite, silence and noise. The evaluation of a rule to clas-
⁷⁰¹ sify a silence only requires the comparison of the sample counter k_T,
⁷⁰² which involve 100 operations/s. To evaluate the remaining rules, the
⁷⁰³ algorithm checks the conditions that define each type of event. There-
⁷⁰⁴ fore, the overall computational complexity for each of these rules is 500
⁷⁰⁵ operations/s. Since all rules are evaluated at every event, the overall
⁷⁰⁶ complexity for this task is 2100 operations/s.

⁷⁰⁷ A linear complexity for CBRTA is given by the total number of opera-
⁷⁰⁸ tions per second that are required to be executed for an IIR low-pass filter
⁷⁰⁹ implementation, as follows:

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

Appendix B. CBHMM complexity analysis

⁷¹¹ The cost of each step of the CBHMM algorithm presented by Milone et al.
⁷¹² (2012) is evaluated as a function of the number of samples n to be analyzed
⁷¹³ per second ($f_{CBHMM}(n)$)), where n depends on the sampling frequency. The
⁷¹⁴ corresponding system was implemented by the authors using the HTK toolkit
⁷¹⁵ (Young et al., 1997).

⁷¹⁶ The signal will be analyzed using overlapped windows. Window duration
⁷¹⁷ w_L and window step w_S were defined as 60 ms and 40 ms, respectively.
⁷¹⁸ Regardless of the sampling frequency of input audio the number of windows
⁷¹⁹ n_w to be processed per second is

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

⁷²⁰

⁷²¹ where s_L is the duration of the segment of signal to analyze. The number of
⁷²² samples n_S to be processed per window depends on the number of samples
⁷²³ to be analyzed as

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

⁷²⁴ Recognition processes can be separated into two main stages: i) feature
⁷²⁵ extraction and ii) classification. During the feature extraction stage, each
⁷²⁶ window is analyzed with the same exact processes. The following complexity
⁷²⁷ analysis will be done for a single window of n_S samples:

⁷²⁸ 1. **Pre-emphasis filter**: a simple pre-processing operation emphasizes
⁷²⁹ the signal by applying a first order difference equation, that involves
⁷³⁰ an addition and a multiplication ($2n_S$ operations).

⁷³¹ 2. **Windowing**: a Hamming window function is applied to pre-processed
⁷³² signal. This operation requires a multiplication for each sample of the
⁷³³ window (n_S operations).

⁷³⁴ 3. **Window energy**: is a numeric value obtained from windowed signal
⁷³⁵ that will be part of the feature vector. It requires $2n_S$ operations.

40

4. **Fourier transform**: the windowed signal is transformed using a fast Fourier transform, and magnitude is then taken. Complexity of these computations are $n_S\,log(n_S)$ and n_S operations, respectively.

5. **Filterbank analysis**: is a simple transform based on a bank of triangular filters designed to give approximately equal resolution on a mel-scale. Each Fourier magnitude coefficient is multiplied by the corresponding filter gain and the results are then accumulated. Thus, each bin holds a weighted sum representing the spectral magnitude in that filterbank channel. Ten filters that spread between 0 and 500 Hz were selected by Milone et al. (2012). The complexity is a function of the maximum length of the filter F_{ML}, it is at most $20F_{ML}$ operations. Because it is clear that $F_{ML} \ll n_S$, then this operation should not be the most computationally expensive. It could be established a computational complexity of $20n_S$ operations as upper bound.

6. **Logarithm**: is applied to each channel parameter of the filterbank. This requires 10 operations (10 operations).

7. **Deltas**: a feature vector is composed by 22 elements is arranged by 10 log-filterbank parameters, window energy, deltas of log-filterbank parameters, and delta of energy. Deltas computation requires 11 additional operations.

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

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

This number must be multiplied by n_w to obtain the complete number of

sinc(i) Research Center for Signals, Systems and Computational Intelligence (fich.unl.edu.ar/sinc)
J. O. Chelotti, S. R. Vanrell, D. H. Milone, S.A Utsumi, J. Galli, C. Cangiano, H. L. Rufiner & L. Giovanini; "A real-time algorithm for acoustic monitoring of ingestive behavior of grazing cattle"
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operations in the feature extraction stage for one second of audio. The cost of classification stage is revised below under the same assumption that one second of audio must be processed.

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

Step (i) was already addressed in feature extraction stage. To perform step (ii) the Viterbi algorithm is used. This algorithm requires on the order of VQ^2T computations, where V is the number of words, Q is the number of states in each model, and T is the length of the feature vectors sequence (Rabiner and Juang, 1993). Since $V = 3$ (chew, bite and chewbite), $Q = 4$ and $T = 24.5$ (number of windows per second), the viterbi computations needed are $VQ^2T = 1,176$. Each Viterbi computation requires one multiplication, one addition, and a likelihood calculation (at least $M(d + d^2)$ operations (Duda, Hart, pp. 111), where $d = 22$ is the number of features, and the number of mixed gaussians is $M = 90$). Then, the operations needed in step (ii) are $VQ^2T(2 + M(d + d^2)) = 53,557,392$. Operations performed in step (iii) are just 3 comparisons to obtain the highest likelihood. Therefore, the number of operations performed in classification stage is determined by step

784 (ii).

785   The algorithm CBHMM shows a superlinear complexity where the total

786 number of operations per second of signal required to execute this algorithm

787 is the sum of feature extraction and classification stage costs, as follows:

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

$$(B.4)$$

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44

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