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The Classification of Sheep and Goat Feeding Phases from Acoustic Signals of Jaw Sounds

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Abstract - This paper describes and documents investigatory work for the detection and measurement of sheep rumination and mastication time periods from jaw sounds transmitted through the skull. The rumination and mastication time periods were determined by a neural network classifier using a combination of time and frequency domain features extracted from successive 10 second acoustic signal lengths. It is shown that spectral features contain most of the information required for good classification.

1. Introduction

Animal nutritionists need accurate data on the time spent by ruminants which include sheep, goats and cattle in mastication and rumination phases over long periods. This data can be gathered by humans manually by listening to recordings of jaw movements. However, this is a tedious task which is very time consuming and subject to error. Consequently, an accurate automated system is required to process the large amounts of acoustic data with minimum error. The main processing task is the ability to classify time periods according to the three main feeding phases of resting, mastication and rumination. A suitable classifier for this problem is an Artificial Neural Network (ANN) fed by relevant time domain and frequency domain features extracted from the jaw sounds.

Investigations based on preliminary data gathered from a Tasmanian study [1] and other studies showed that it is feasible to achieve the required rumination and mastication classifications using frequency spectral information over ten-second blocks of time. An undergraduate student project ("Classification of Sheep Feeding Phases", Michael Dragojevic 1994, Department of Electrical and Electronics Engineering, The University of Western Australia) showed that adequate classification was also achievable using the spectral information in a single chew. This work did eventually result in the development of a real-time system for the characterisation of sheep feeding phases [2].

2. Frequency Domain Features

The initial study was conducted with data supplied from [1]. The data consisted of nine minutes and 42 seconds of audio cassette recording of a sheep B ruminating (146 seconds), a goat R ruminating (155 seconds), a goat P masticating (134 seconds) and a sheep A masticating (147 seconds). After initial investigation it was found there was little significant signal energy in the recording above 1,680 Hz so the recordings were digitised at a sample rate of 3,360 Hz with 14 bit precision. Independent signal records of 33,792 points each were taken from the four categories to build up data for category samples. Each record represented 10.057 seconds of continuous recording and it was subdivided into 33 contiguous frames of 1,024 points each. Examples of sheep mastication and ruminating records are shown in Figures 1 and 2.

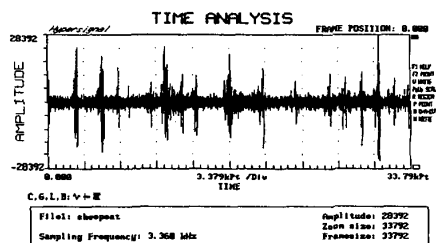


Figure 1. Sheep Mastication Time Plot

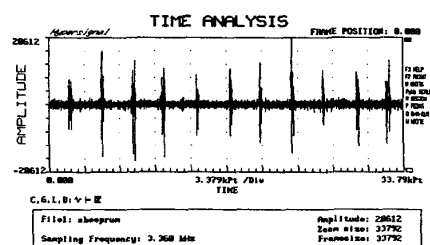


Figure 2. Sheep Ruminating Time Plot

Feature vectors for category classification were derived from the power spectral estimate (PSE) of each 33,792 point record. Firstly, 66 1,024 point frames were Blackman windowed to taper the values at the beginning and end of the frame to zero. The 66 frames were taken progressively through the record, each having a 512 point overlap with the previous frame. A 1,024 point

Fast Fourier Transform (FFT) was performed on each frame. The magnitude squared values of each frame were averaged over the 66 frames to produce a PSE of 512 points spanning 0 to 1,680 Hz. Each point in the PSE represented a 3.28125 Hz frequency band. Next, the square root of the PSE was performed to produce the FFT magnitude which was divided into nine equally spaced frequency bands of 167.34375 Hz each. This choice was based on visual inspection of the PSE plots which indicated that most of these bands had differing values for the four categories. Finally, the frequency values in each band were averaged and used to create a normalised nine dimensional feature vector for category classification.

The Probabilistic Neural Network (PNN) [3] was used to perform the classification task because it performs well with relatively few independent feature vectors and it is quick and easy to train. For initial testing the following numbers of feature vectors for each of the four categories were extracted from relatively noiseless parts of the recording:

Class 1, Sheep B ruminating - 9
 Class 2, Goat R ruminating - 12
 Class 3, Sheep P masticating - 8
 Class 4, Goat A masticating - 4

Due to the relatively small numbers of feature vectors (33) the PNN was used in the holdout test mode to maximise the results. In the holdout test mode each vector is taken out of the vector set in turn and tested against the remainder. The PNN achieved 100% classification accuracy for sigma between 0.014 and 0.071.

In the next sample set some mostly noisy samples were added to the relatively noiseless samples above. The main type of noises were the banging of metal feed trays and occasional animal bleating during the mastication phases only. The rumination recordings had no loud noises in them except for occasional low level metal feed tray banging. The numbers of feature vectors were as follows:

Class 1, Sheep B ruminating - 11
 Class 2, Goat R ruminating - 12
 Class 3, Sheep P masticating - 11
 Class 4, Goat A masticating - 12

Once again the PNN was used in the holdout test mode and it achieved 100% classification for sigma between 0.028 and 0.049.

These results showed that it was possible to positively identify sheep B ruminating, goat R ruminating, sheep P masticating and goat A masticating from the audio recordings. The preprocessing and classification method described above was able to effectively perform the

discrimination even when significant feed bin banging and bleating noises are mixed with feeding sounds.

Dragojevic used an Autoregressive Power Spectral Density (APSD) estimation technique to extract the spectral features from each individual chew signal of 512 points sampled at a rate of 3,360 Hz. He used 12 spectral bins to create the feature vectors and tested various neural network classifiers. All data were taken from a single sheep fed clover. The training data set consisted of the following numbers of feature vectors:

Class 1, Sheep ruminating chew - 175
 Class 2, Sheep masticating chew - 175
 Class 3, Random Gaussian noise - 46

The testing data set consisted of samples of:

Class 1, Sheep ruminating chew - 100
 Class 2, Sheep masticating chew - 100
 Class 3, Random Gaussian noise - 100

After training he achieved a 93.0% accuracy on the testing set using a PNN classifier.

Both these preliminary studies provided enough confidence in the belief that there is sufficient spectral information in the chewing sounds to achieve satisfactory discrimination between sheep mastication and rumination phases.

3. Bandwidth Filtering

Following these preliminary classification tests more extensive field trials were conducted where a large amount of data were gathered. This data included jaw sounds from various sheep exposed to a number of different pastures including clover-dominant pasture and mixed pastures of clover and grasses. During the field trials there were a number of different noise signals that were mixed in with the jaw sound signals, including:

- 1) Sheep noises, eg. bleating, jumping, rubbing.
- 2) Environmental, eg. wind and rain, aeroplane, vehicle and machinery, human voices and movement, and wild life.
- 3) Electrical, eg. static, radio signal break in and break out, radio signal whistle and howl.

Due to this large range of background noise it was decided to bandpass filter the signal in a band between seven Hz and 212 Hz. This bandwidth represents the frequency band where most of the information related to chewing is found and which excludes many of the background noises and interferences. After the bandpass filter the signals were digitised via a 12 bit Analog to Digital Converter (ADCs) sampling at 400 Hz.

4. Time and Frequency Domain Features

Although it seemed possible to develop an adequate classification system based totally on frequency domain information it was considered that adding time domain information may improve the performance. There are very clear and relevant time domain features related to the chewing intervals and chewing frequency as well as chewing strength. Therefore, it was decided to construct a classification feature vector which was composed of chewing period information, chewing energy and frequency spectrum information. There were a total of seven chewing period features, five chewing energy features and eight frequency spectrum features selected. These were used to form a twenty one coefficient vector x as follows:

Chewing Period Features within 10 Second Blocks

Chew pulse period statistics were computed only if there were more than 2 chew pulses in the 10 signal block.

- $x[1] = (\text{no. of chews} / 30.0)$, if max chew period $\neq 0$
- $x[2] = (\text{mean chew period} / \text{max chew period})$, if mean chew period $\neq 0$
- $x[3] = (\text{median chew period} / \text{mean chew period})$
- $x[4] = (0.1 \text{ SD of chew periods} / \text{mean chew period})$
- $x[5] = (\text{min chew period} / \text{mean chew period})$
- $x[6] = (\text{mean chew period} / 20.0)$, if max chew period $\neq 0$
- $x[7] = (\text{mean chew period} / \text{maximum chew period})$

Chewing Energy Features within 10 Second Blocks

If standard deviation (SD) of chew energy $\neq 0$ then:

- $x[8] = (10.0 \times \text{mean chew energy} / \text{SD of chew energy})$, if mean chew energy $\neq 0$
- $x[9] = (10.0 \times \text{minimum chew energy} / \text{mean chew energy})$
- $x[10] = (\text{mean chew energy} / 2000.0)$, if maximum chew energy pulse height $\neq 0$
- $x[11] = (\text{mean chew energy pulse height} / \text{maximum chew energy pulse height})$, if SD of chew energy pulse heights $\neq 0$
- $x[12] = (\text{mean chew energy pulse height} / \text{SD of chew energy pulse heights})$, if mean chew energy pulse height $\neq 0$
- $x[13] = (\text{minimum chew energy pulse height} / \text{mean chew energy pulse height})$

Spectral Features within 10 Second Blocks

- $x[14] = (\text{band 1 (0-25 Hz)} / \text{max. band energy})$
- $x[15] = (\text{band 2 (25-50 Hz)} / \text{max. band energy})$
- $x[16] = (\text{band 3 (50-75 Hz)} / \text{max. band energy})$
- $x[17] = (\text{band 4 (75-100 Hz)} / \text{max. band energy})$
- $x[18] = (\text{band 5 (100-125 Hz)} / \text{max. band energy})$
- $x[19] = (\text{band 6 (125-150 Hz)} / \text{max. band energy})$

- $x[20] = (\text{band 7 (150-175 Hz)} / \text{max. band energy})$
- $x[21] = (\text{band 8 (175-200 Hz)} / \text{max. band energy})$

5. Classifier Test Results

A number of classifier tests were performed using the 21 time and frequency domain features defined above. The first neural network classifier which was used to categorise the feeding phases was a Multi-layer Perceptron (MLP) with 21 input, 7 hidden and 3 output nodes. It required 50,000 training iterations at a gain setting of 0.001 and momentum setting of 0.0001 to achieve a satisfactory classifier performance. The MLP (21-7-3) neural network classifier was trained with a wide range of data taken from various field trials and different sheep fed clover-dominant pasture as well as mixed clover and grass pastures. The resulting category confusion matrices for independent training and testing data sets were as shown in Tables I and II.

TABLE I

	resting	masticating	ruminating
True resting	900	0	0
True masticating	0	753	68
True ruminating	1	105	1169

94.19% training accuracy

TABLE II

	resting	masticating	ruminating
True resting	900	0	0
True masticating	0	742	79
True ruminating	2	117	1156

93.39% testing accuracy

The same data with all 21 features was tested using a PNN classifier. Table III shows the resulting category confusion matrix and classification accuracy.

The σ specified in The tables III, IV and V is the single optimising parameter which is chosen during PNN training. It represents the common bandwidth of Gaussian radial basis functions centred at each and every training vector in the network structure. The PNN works by performing nonparametric feature vector density estimation through the use of a common bandwidth (σ) radial kernel. If there are enough training vectors for each class the network is able to provide a very good density estimate for each class. Thus the PNN approximates a Bayesian classifier as the number of training vectors increases and the bandwidth reduces. The only real disadvantage of this is that the network

size becomes a direct function of the number of training vectors.

TABLE III

	resting	masticating	ruminating
True resting	900	0	0
True masticating	0	749	72
True ruminating	2	124	1149

93.39% testing accuracy, $\sigma = 0.124$

The classification results achieved with the MLP and PNN classifiers for all 21 features were very similar.

Next, the data with only the first seven chewing period features was tested using a PNN classifier. Table IV shows the resulting category confusion matrix and classification accuracy.

TABLE IV

	resting	masticating	ruminating
True resting	900	0	0
True masticating	0	761	60
True ruminating	2	129	1144

93.62% testing accuracy, $\sigma = 0.05$

The results using only the chewing period features were comparable with that of all twenty one features. It was subsequently discovered that the chewing energy features, features eight to thirteen, were not overly effective. They alone produced a classification accuracy of only 80.94%. However, the spectral features alone, features fourteen to twenty one, produced very good results as shown in Table V.

TABLE V

	resting	masticating	ruminating
True resting	900	0	0
True masticating	0	800	21
True ruminating	2	95	1178

96.06% testing accuracy, $\sigma = 0.004$

The accuracy, 96.06%, using spectral features in the ten second blocks was higher than that achieved by Dragojevic, 93.0%, using spectral features of individual chews only. Clearly, the frequency information related to the chewing sequences added vital classification information as one would expect.

Combining the chewing period and spectral features produced the results shown in Table VI.

TABLE VI

	resting	masticating	ruminating
True resting	900	0	0
True masticating	0	777	44
True ruminating	2	91	1182

95.43% testing accuracy, $\sigma = 0.05$

Adding the spectral features to the chewing period features strengthened the discrimination achieved with the chewing period features alone.

For all combinations of features tested the accuracy of mastication detection was slightly better than rumination detection.

6. Conclusions

The tests performed in this experiment indicate that spectral features, within a frequency band of seven Hz to 212 Hz in 10 second signal blocks, alone give very good discrimination between mastication and rumination. This is very convenient as spectral features are relatively easy to implement in a real-time system. However, in a real system it would also be necessary to identify the individual chews for adequate feeding statistics analysis. It is also possible to perform adequate discrimination between mastication and rumination using features extracted from chewing period features alone. Therefore it is possible to design a system based on either chewing period features or both chewing period and spectral features.

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