Detection of Rain in Acoustic Recordings of the Environment

Meriem Ferroudj[1], Anthony Truskinger[2], Michael Towsey[2], Liang Zhang[2], Jinglan Zhang[2], and Paul Roe[2]

[1,2]School of Electrical Engineering and Computer Science
Queensland University of Technology, Brisbane, Australia

{meriem.ferroudj}@connect.qut.edu.au
{Anthony Truskinger, l68.zhang}@connect.qut.edu.au
{m.towsey, jinglan.zhang, p.roe}@qut.edu.au

Abstract. Environmental monitoring has become increasingly important due to the significant impact of human activities and climate change on biodiversity. Environmental sound sources such as rain and insect vocalizations are a rich and underexploited source of information in environmental audio recordings. This paper is concerned with the classification of rain within acoustic sensor recordings. We present the novel application of a set of features for classifying environmental acoustics: acoustic entropy, the acoustic complexity index, spectral cover, and background noise. In order to improve the performance of the rain classification system we automatically classify segments of environmental recordings into the classes of *heavy rain* or *non-rain*. A decision tree classifier is experientially compared with other classifiers. The experimental results show that our system is effective in classifying segments of environmental audio recordings with an accuracy of 93% for the binary classification of *heavy rain*/*non-rain*.

Keywords: Audio classification; Audio features; Feature extraction; Feature selection; Environmental sound sources; Regression.

Introduction

Acoustic sensor recordings are a rich and underexploited source of information in environmental monitoring. Acoustic data are highly variable and contain much background noise. Hence, it is hard to describe the many sources of environmental sound by using common audio features. Defining suitable features for environmental sounds is an important problem in an automatic acoustic classification system. Noise is defined simply as any unwanted signal in a data source. For some applications, background noise such as rain, is considered uninteresting and often discarded. However, in this study, detecting rainy periods in acoustic data is the goal as automatic recognition of these sounds can be used to help avoid them in animal call recognition or help analyze the relationship between rainy weather and animal call activities. Thus rain in audio recordings is considered signal rather than background noise in this research. Much of the background noise in environmental recordings is of geophonic (generated from wind, rain, rustling of leaves, etc.) or biophonic (generated from cicadas, birds, and other fauna). In this work, the definition of background noise is restricted to signals with constant acoustic energy throughout the duration of the recording.

Our bioacoustics research group [1] has researched and deployed different types of acoustic sensors and collected more than 24TB of acoustic data. As expected, the acoustic data collected is not free from background noise. For ecologists, rain is considered background noise when they are estimating species richness by sampling very long acoustic recordings. Avoiding periods with much background noise (and typically less faunal vocalization) improves the efficiency of audio sampling. Additionally, the presence of rain makes it harder to annotate avian vocalizations in audio data. Whether fauna are vocalizing or not, ecologists will typically avoid listening to rainy sections of audio recordings. Labelling these rainy periods will increase the efficiency and effectiveness of bioacoustic data analysis. The ability to detect rainy periods may also assist other analysis efforts, such as Anuran vocalization detection. We approached the rain detection in acoustic sensor recordings problem as a classification task.

The contribution of this research includes: (1) a method for classifying rainy periods of audio data captured by environmental sensors, (2) an investigation of the effectiveness of combining different features for classification, (3) a comparison of the performance of different classifiers, and (4) an exploration of a variety of regression algorithms to predict rain in long duration audio recordings.

The rest of the paper is organized as follows: Section 2 summarizes related work on environmental sounds classification. Section 3 describes the composition of different audio datasets for the experiments, the feature set, and a variety of classifiers used for rain classification. Section 4 describes the experiments conducted and evaluates the performance of a variety of audio features and classifiers by comparison. Finally, Section 5 concludes the paper.

Related Work

There has been much effort to improve the accuracy of the classification and recognition of audio data using different features and classifiers. Based on the work of Li [2], audio features can be divided into two types: *Mel-frequency cepstral coefficients* (MFCCs) and perceptual features (*zero crossing rates* (ZCR), *spectrum flux* (SF), *band periodicity* (BP), *noise frame ratio* (NFR), *spectral roll-off*, *low energy rate*, *brightness*, and *pitch*) [3].

MFCC features are modelled based on the shape of the overall spectrum, making it favorable for representing single sound sources. However, environmental recordings typically contains large varieties of sound sources, including the stridulation of insects, rain drops, that are characterized by narrow spectral peaks, all of which MFCCs are unable to encode effectively[4].

Chu et al. [5] proposed a novel feature extraction method that uses a *matching pursuit* (MP) algorithm to select a small set of time-frequency features to analyze environment sounds. They adopted a *Gaussian mixture model* (GMM) classifier for classifying 14 types of environmental sounds. In their study, they have found that using MFCCs and MP features separately produce poor accuracy rates. They demonstrated that combining MFCCs and MP-based features produces a better accuracy rate (83.9%) for discriminating fourteen classes. They concluded that MP-based features could be used to supplement frequency domain features (like MFCCs) to yield higher automatic recognition accuracy for environmental sounds. Li [6] stated that the matching pursuit algorithm is a good technique for feature extraction, which can describe environmental sounds well. They have also demonstrated that the combination of the features MP and MFCCs achieves a high accuracy rate. They used a *support vector machine* (SVM) as a classifier for their environmental sound classification system and achieved an accuracy rate of 92%. Barkana et al. [7] explored the classification of a limited number of environmental sound sources, including those produced by engines, restaurants, and rain. They proposed a new feature extraction technique based on the fundamental frequency (pitch) of the sound. They used two different classifiers, support vector machines and *k-means clustering* to classify the different classes. The classifiers used in their research achieved recognition rates of 95.4% and 92.8%, respectively.

Although much research has been published on environmental sound source classification, little research has been done for rain classification. We evaluate five features intended to describe rain in audio recordings: *acoustic entropy (H)* for which we calculated *spectral* and *temporal entropy (Hf, Ht)* respectively, *Acoustic complexity index* (ACI), *background noise (BgN)* and *spectral cover (SC)*, which have been used for environmental monitoring but not extensively applied and evaluated for rain detection and classification.

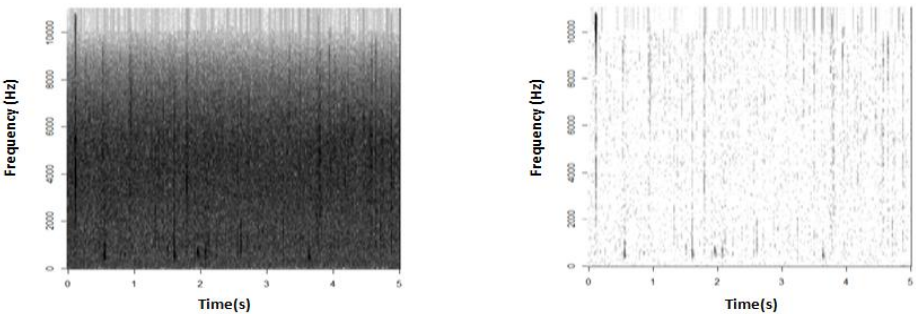
Methods

Our work differs from the existing works on classifying environmental sounds in that new type of features and different classifiers. We used raw audio data recorded by sensors deployed in the field.

Preprocessing of audio recordings

Recordings were sampled at 22050Hz with a 16-bit resolution. They were stored in WAV format. In order to generate a spectrogram (shown in Fig. 1.(a) where x-axis is in seconds, y-axis is in Hertz and the grey color represents the energy), the audio recording was divided into frames of 512 samples (23.5ms), overlapping by 50% (11.6ms). A Hamming window function was applied to each frame prior to performing a Fast Fourier Transform (FFT), which yielded amplitudes values for 256 frequency bins, each spanning 43.07Hz. The spectrum was smoothed with a moving average window of width three. Spectrograms were “noise reduced” using a modification of adaptive level equalization [8] applied to every frequency bin independently

[9]. Adaptive level equalization has the effect of removing continuous background acoustic activity and setting that level to zero amplitude. Thus it becomes possible to define a threshold for the detection of an acoustic event that spans multiple frequency bins. The intensity values in the spectrograms were not converted to decibels in order to preserve values appropriate for subsequent calculations of entropy. This approach is also consistent with the work of Sueur and Farina [10, 11]. Fig. 1 shows an example of rainy data, pre and post noise removal.



(a) Rain before noise removal

(b) Rain after noise removal

Fig. 1. Rain before and after noise removal

Datasets preparation

We have selected two different datasets: *Dataset A* and *Dataset B*.

- *Dataset A (manual segments labelling)*: Recordings were obtained by use of acoustic sensors from the *Samford Ecological Research Facility* (*SERF*) in bushland on the outskirts of Brisbane city, Queensland, Australia. To make *dataset A* more realistic, the recordings were selected from: different days, different time in the day, and different sites (33 days and four sites precisely). We used an audio browser which uses acoustic indices developed by Towsey [12] to scan through the each 24 hour recording to find segments of interest. Interesting segments were examined in *Audacity*, which allowed for aural and visual inspection of the signal. *Dataset A* contains 998 five seconds segments. Five seconds was chosen empirically (based on observed patterns of rain starting and stopping) as the classification resolution for this experiment. Each segment is manually labeled into one of seven classes: *heavy rain*, *cicada chorus*, *bird calls*, *frog calls*, *koala bellow*, *light rain*, and *low-activity (night time)*. Table 1 shows the composition of the Dataset A.

When inspecting our data, classes were created to discriminate between the types of acoustic data that were observed. For example most of the recordings include cicada choruses which are continuous (much like rain) but have different acoustic properties in the time-frequency domain. Rain produces two different visual features in a spectrogram: The first one is a general increase in background noise. The second distinct feature is vertical broadband lines on the spectrograms; these are percussive drops on the audio senor's housing. Cicadas occupy a certain frequency band 2-4kHz. Birds occupy a different frequency bands and species have different call structure (oscillation, static harmonics, lines, and other structures). The acoustic Entropy feature can describe this information and constitutes the main feature for classifying these classes. While labelling the training data for rain events, other acoustic classes were also labelled, originally to assist in explaining the classification results. Additionally labelled events include periods of night time /low activity.

Table 1. Composition of Dataset A

<table>
<tr><th rowspan="2">Classes</th><th rowspan="2">Count</th><th>Dataset A.1</th><th>Dataset A.2</th><th>Dataset A.3</th></tr>
<tr><th>2 Class-problem</th><th>3 Class-problem</th><th>4 Class-problem</th></tr>
<tr><td>Heavy rain</td><td>244</td><td>1</td><td>1</td><td>1</td></tr>
<tr><td>Cicada chorus</td><td>193</td><td rowspan="6">2</td><td>2</td><td>2</td></tr>
<tr><td>Bird calls</td><td>483</td><td rowspan="5">3</td><td rowspan="3">3</td></tr>
<tr><td>Frog calls</td><td>16</td></tr>
<tr><td>Koala bellow</td><td>2</td></tr>
<tr><td>Light rain</td><td>17</td><td rowspan="2">4</td></tr>
<tr><td>Low-activity</td><td>43</td></tr>
<tr><td>Total</td><td>998</td><td>244/754</td><td>244/193/561</td><td>244/193/501/60</td></tr>
</table>

- *Dataset B (long audio recording):* is a 24-hour MP3 recording derived from *SERF* (core vegetation plot site), on the 13th April 2013. The upper part of Fig. 2 is a false-color spectrogram of a 24-hour recording obtained using the method described by Towsey et al [13]. The x-axis extends from midnight to midnight. Since the x-axis scale is one pixel-column per minute, a greater than 2000x compression is achieved over the standard spectrogram. Note that the frequency scale is unchanged. The lower part of Fig. 2 is a grey-scale representation of the content of the environment of that particular day. The image shows that the source audio does not only contain rain, but also contain crickets, as well as other faunal vocalizations.
- *Ground truth:* The ground truth used is weather data obtained from the weather station located at the same Ecological Research Facility. The model of the weather station is a Wireless Vantage Pro2 (6152). Rain is measured in mm i.e. the number of mm collected in a calibrated vessel over a logging period (in this case five minutes).

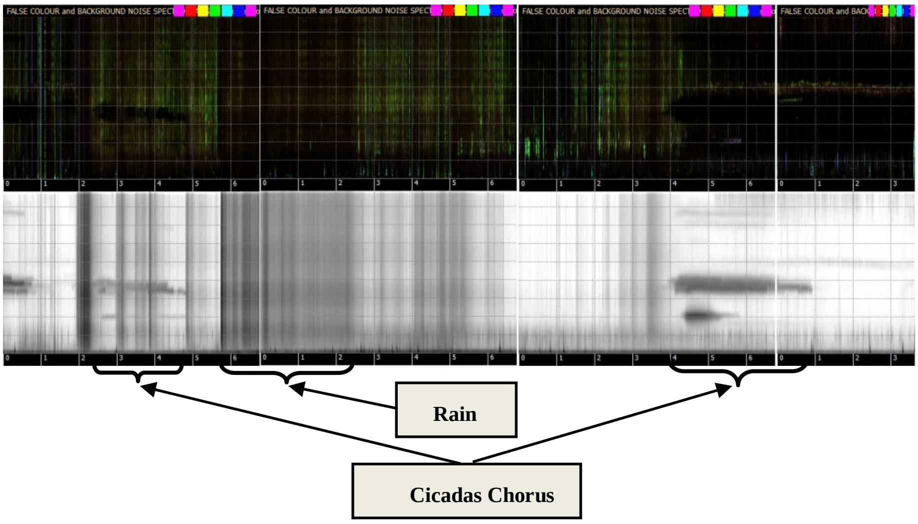


Fig. 2. Visualization of 24-hour long duration acoustic recordings of the environment

The steps taken to prepare the *Dataset B* are summarized in the following diagram:

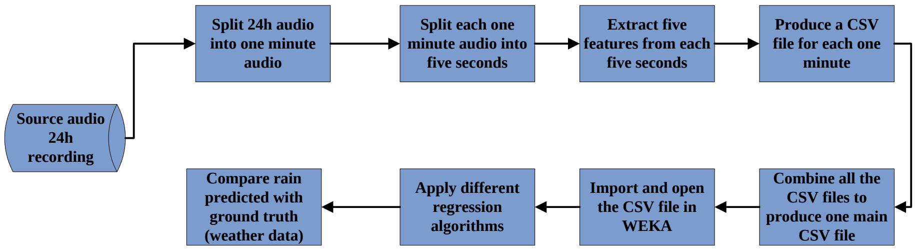


Fig. 3. Preparation process for the 24-hour long duration dataset

Feature Selection

Feature selection is crucial to obtain high classification accuracy. We choose and extract five features from environmental sounds: (1) acoustic entropy (H) for which we calculated spectral and temporal entropy (Hf, Ht) respectively, (2) Acoustic complexity index (ACI), (3) background noise and (4) spectral cover (SC).

Acoustic entropy is a measure of the dispersal of acoustic energy within a recording, either through time or frequency bands [10]. Sueur et al. acknowledge the difficulty of building individual species recognizers and therefore turn to indirect measures of biodiversity, making the simple assumption that the number of vocalizing species positively correlates with the acoustic heterogeneity of audio data within a locality. They conclude that acoustic entropy does correlate with acoustic heterogeneity.

The temporal entropy index H_t and the spectral entropy index H_f are computed following their definitions in [10] :

$$H_t = -\sum_{t=1}^{n} A(t) \times \log_2 (A(t)) \times \log_2 (n)^{-1} \quad (1)$$

$$H_f = -\sum_{f=1}^{N} S(f) \times log_2 \left(S(f)\right) \times log_2(n)^{-1} \quad (2)$$

where n is the length of the signal in number of digitized points;

$A(t)$ is the probability mass function of the amplitude envelope; and

$S(f)$ is the probability mass function of the mean spectrum calculated using a short term Fourier transform (STFT) along the signal with non-overlapping Hamming window of $N = 512$ points.

The Acoustic complexity index (ACI) is based on the assumption that bird sounds are characterized by having a great change in the intensity, even in short period of time and in a single frequency bin. However, environmental sounds have smaller changes in intensity values, which mean the difference in the intensity values between two successive frames t and $t + 1$ is small. For example, bird or cicada sounds have a significant change in intensity between frames within a single frequency-bin producing a high value for ACI. For noise like wind, rain, and mechanical sources (like airplane engines), the change in the intensity is not large; the variation in the intensity is approximately constant. The value for the ACI feature for these sound sources is expected to be low. We reason that ACI may be a suitable discriminator for rain/non-rain classification and as such we chose ACI as one of the main features for this study.

The background noise (BgN) is estimated from the wave envelope using a modification of the method of Lamel [8] as described by Towsey [12] (the value is expressed in amplitude).

The spectral cover calculates the fraction of spectrogram cells where the spectral amplitude exceeds a threshold $\theta = 0.015$. The suitability of this threshold was determined by trial and error.

Classifiers

The classifiers we use in these experiments are part of Weka (Waikato Environment for Knowledge Analysis) [14]. Weka is a collection of machine learning algorithms for data mining tasks written in Java.

Algorithms used for classification.

Using the features described in Section.3.2, we evaluate a variety of algorithms for supervised learning which are described briefly below:

- *Naive Bayes:* It is a simple probabilistic classifier based on Bayes rule.
- IBK (instance-based method on k-NN neighbor).

- Sequential minimal optimization (SMO) which is an implementation of support vector machines (SVM) in Weka.
- J48 algorithm is the Weka implementation of the C4.5 top-down decision tree learner proposed by Quinlan [15].

Algorithms used for regression.

The algorithms employed for rain detection using regression techniques are outlined below:

- *Linear regression (LR):* The Linear Regression algorithm performs standard least squares regression to identify linear relations in the training data.
- *M5P:* or M5Prime algorithm generates M5 model trees using the M5 algorithm, which was introduced by Wang and Witten [16] and enhances the original M5 algorithm by Quinlan [15].
- *RepTree:* This algorithm is a fast tree learner. It Builds a decision/regression tree using information gain/variance and prunes it using reduced-error pruning.
- *Multi-Layer-Perceptron (MLP):* This classifier uses back-propagation to classify instances.
- *Decision table (DTB):* This algorithm builds and uses a simple decision table majority classifier.

Results and discussion

Experiment 1: Binary Classification.

The *heavy rain* events were classified by C4.5 decision tree (DT) classifier (J48 in Weka). The Dataset A.1 contained 244 recordings of *heavy rain* and 754 of *non-rain* (*cicadas*, *birds*, *low-activity*, *koalas*, *frogs* and *light rain*). We performed 10 fold-cross validation on the data. To measure the classification accuracy, we used three measures: precision, recall and accuracy. Precision is defined as $TP/(TP + FP)$, recall as $TP/(TP + FN)$ and accuracy as $(TP + TN)/total\ samples$, where TP, FP, TN, FN are true positive, false positive, true negative, and false negative respectively. The DT classifier was compared with three other classifiers: naive Bayes, Lazy IBK ($k = 1$), and SMO. The purpose of this experiment is to find the best algorithm and the best set or combination of features. We run experiments that use different combinations of features and different classifiers to classify environmental sounds into two classes as shown in Table 1.

Table 2 provides a summary of the results that we received from each algorithm for the two classes (*heavy rain*/*non-rain*). It can be observed that the average classification accuracy of the Ht+Hf+ACI+BgN+SC features is the best. We noticed that combining only temporal and spectral entropy produces low classification accuracy in differentiating the classes. It is noticeable that combining more than two features increases the accuracy rate. From Table 2, we can see also that DT and lazy IBK perform better than the other algorithms. Despite similar performance between IBK and DT, we conclude that a DT is the best classifier because the classification rules are easily extracted and repurposed. The Ht+Hf+ACI+BgN+SC is the best feature set in our experiment. The classification accuracy achieved is 93%.

Table 2. Total accuracy rate (%) of Dataset A.1 using different types of classifiers and features

Feature Type	**Accuracy Rate (%)**			
	NB	**Lazy IBK**	**SMO**	**DT**
Ht+Hf	89	84	78	88
Ht+Hf +ACI	91	90	91	92
Ht+Hf +BgN	77	87	78	91
ACI+BgN+SC	91	91	92	92
Ht+Hf +ACI+BgN	90	92	91	92
Ht+Hf +ACI+BgN+SC	91	93	92	**93**

To the best of our knowledge, there are no existing techniques that have been specifically developed for rain/non-rain classification. Therefore, it was not meaningful to quantitatively compare our algorithm to existing techniques or experiments.

Fig. 4 shows the strong relationship between two features namely: acoustic complexity index (ACI) and temporal entropy (Ht) in distinguishing the two classes heavy rain/non rain (binary classification). It is apparent that a linear function can split the majority of instances into two classes.

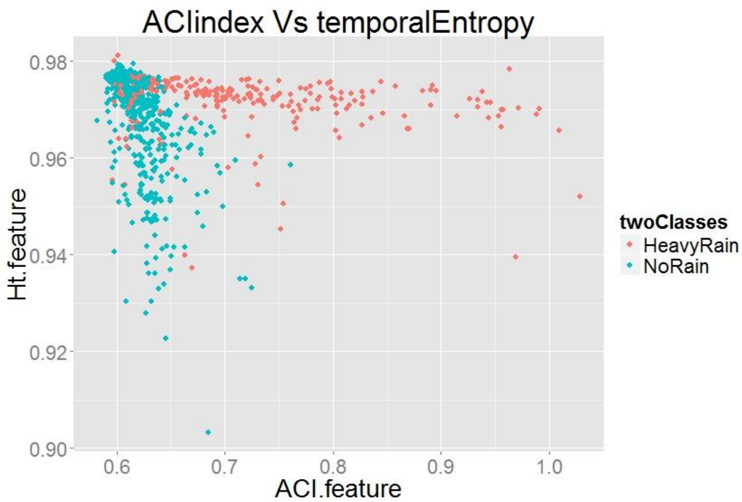


Fig. 4. The relationship between two features in classifying the Dataset A.1 (two-class-problem) with a DT classifier

Experiment 2: Multi-class classification.

The purpose of this experiment is to know whether the same features (as in experiment 1) can be used to distinguish other common sounds in environmental recordings (such as cicadas, animal sounds in general and light rain). To further understand the classification performance, we show results in the form of a confusion matrix, which allows us to observe the degree of confusion among different classes. The confusion matrix given in Table 3 and Table 4 are constructed by applying the DT classifier to the Dataset A.2 (3 class-problem) and Dataset A.3 (4 class-problem); and displaying the number of correctly/incorrectly classified instances. The rows of the matrix denote the environment classes we attempt to classify, and the columns depict classified results. It is immediately apparent that most of the classes achieve a high rate of correctly classified instances. We can see from the matrix that our system can make a distinction between the classes*: heavy rain*, *animal sounds* (*birds, frogs, and koalas*), *cicadas*, and *others* (*low activity and light rain*).

Table 3. Confusion matrix for Dataset A.2 (3 class-problem)

	Animal sounds	**Heavy rain**	**Cicadas**
Animal sounds	**495**	22	48
Heavy rain	43	**194**	7
Cicadas	40	5	**144**

Table 4. Confusion matrix for Dataset A.3 (4 class-problem).

	Animal sounds	**others**	**Heavy rain**	**Cicadas**
Animal sounds	**450**	7	13	30
others	16	**41**	0	4
Heavy rain	48	0	**194**	2
Cicadas	23	9	5	**156**

Experiment 3: 24-hour audio recording.

The aim of this experiment is to show the ability of regression techniques in predicting rain in a 24-hour long recording. We first split the 24-hour recording into one minute audio which yields to 1440 minutes, we further cut each one minute into five seconds, in total $(1440 \times 12 = 17280)$ of five seconds segments. We extracted five features (the same features used in the Experiment 1) from each five seconds of audio, and then we averaged the feature values to produce five minutes blocks. This is done so the weather data, which has a five-minute resolution (287 instances); can be directly used as ground truth data. We have explored a variety of regression techniques in Weka, specifically: M5P, linear regression, RepTrees, Multi-layer-perecptron, and Decision table. Weka provides a variety of error measures, which are based on the differences between the actual and estimated values. Three measures were selected for comparison: *correlation coefficients*, *mean absolute error* (MAE), and *root mean square error* (RMSE).

- MAE and RMSE are regularly used as standard statistical metric to measure the model performance.
- The *correlation coefficient* measures the degree of correlation between the actual and estimated values. Table 3 summarizes three different statistical measures (MAE, RMSE and coefficient correlation) for the different algorithms using *10 fold cross-validation*.

M5P proved the best results in our case because of the nature of the problem considered as well as the type of data we are using. M5P is a decision tree for numeric prediction that stores a linear regression at each leaf to predict the class value of instances that reach that leaf. M5P is found to be a good technique to handle numerical class attributes. In our case, the class attribute represents the amount of rain in mm over five minute periods; therefore, M5P is more suited for this classification problem than other techniques. The M5P tree model developed with *10 fold* cross-validation was realized to be the best model that predicted rain in the 24h-recording with RMSE of 0.14, and a correlation coefficient of the measured and predicted rain of 0.78.

Table 3. Correlation coefficients between actual and predicted rain, MAE and RMSE

Algorithms	**Correlation coefficients**	**MAE**	**RMSE**
M5P	**0.78**	0.07	0.14
LR	0.75	0.08	0.15
RepTree	0.68	0.08	0.17
MLP	0.67	0.11	0.19
DTB	0.69	0.07	0.17

Fig. 5 illustrates the power of the M5P algorithm in estimating rain amount in a 24h-long recording. The red, dotted curve represents the M5P estimates while the black, solid curve is the ground truth (actual rain amount from weather station data). It can be seen that the M5P estimates correlate well with the ground truth data.

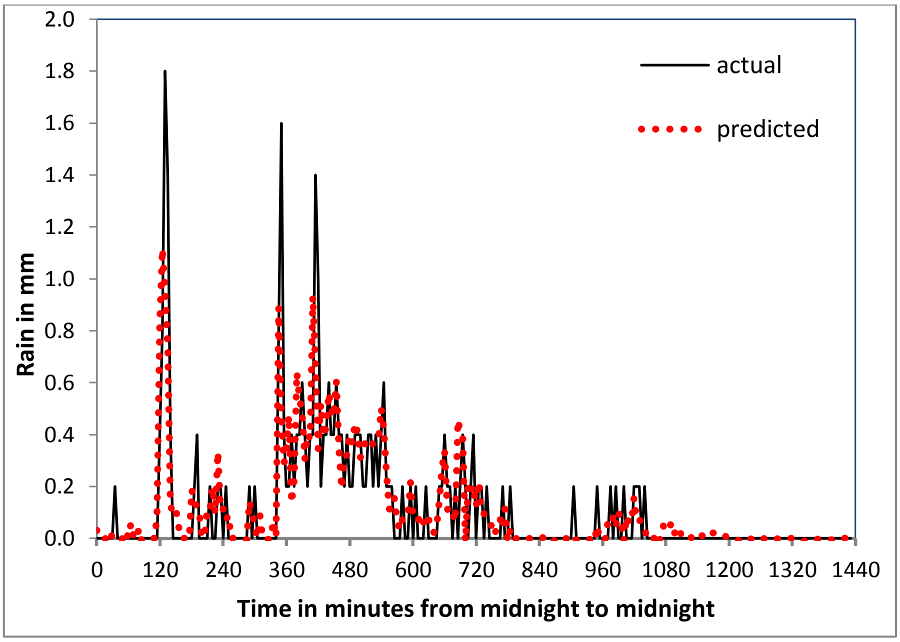


Fig. 5. An example for rain predictions obtained using M5P

Conclusions and future work

This research aims to investigate classification techniques that predict rain in large datasets of audio collected by acoustic sensors.

We have presented an environmental sound classification system using five features and the decision tree classifier. Our comparison experiments show that the method presented is promising. The combination of five features provides better classification performance than using two features.

Another aim of this study is to show the ability of regression techniques in predicting rain using acoustic data in 24-hour long audio recordings collected by sensors in the field. The results showed that M5P has better predictability than the other techniques. Such a prediction tool could prove useful when ecologists are interested in analyzing acoustic audio data, especially when the target fauna such as many Anuran species have a vocalizing relationship with rain events.

As future work, we intend to apply our technique to much larger datasets (months and years) to predict rain in audio recordings.

References

1. Mason, R., et al. *Towards an acoustic environmental observatory*. in *eScience, 2008. eScience'08. IEEE Fourth International Conference on*. 2008. IEEE.
2. Li, S.Z., *Content-based audio classification and retrieval using the nearest feature line method.* Speech and Audio Processing, IEEE Transactions on, 2000. **8**(5): p. 619-625.
3. Rabiner, L. and B.H. Juang, *Fundamentals of speech recognition.* 1993.
4. Chu, S., S. Narayanan, and C.C.J. Kuo, *Environmental sound recognition with time–frequency audio features. IEEE Transactions on Audio, Speech and Language Processing*, 2009. **17**(6): p. 1142-1158.
5. Chu, S., S. Narayanan, and C.C. Jay Kuo. *Environmental sound recognition using MP-based features*. in *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*. 2008. IEEE.
6. Li, Y. *Eco-Environmental Sound Classification Based on Matching Pursuit and Support Vector Machine*. in *Information Engineering and Computer Science (ICIECS), 2010 2nd International Conference on*. 2010. IEEE.
7. Barkana, B.D. and B. Uzkent, *Environmental noise classifier using a new set of feature parameters based on pitch range.* Applied Acoustics, 2011. **72**(11): p. 841-848.
8. Lamel, L., et al., *An improved endpoint detector for isolated word recognition.* IEEE Transactions on Acoustics, Speech and Signal Processing, 1981. **29**(4): p. 777-785.
9. Towsey, M., *Technical report: Noise removal from wave-forms and spectrograms derived from natural recordings of the environment. Brisbane: Queensland University of Technology. Australia* 2013.
10. Sueur, J., et al., *Rapid Acoustic Survey for Biodiversity Appraisal.* PLoS ONE, 2008. **3**(12): p. e4065.
11. Farina, A., N. Pieretti, and L. Piccioli, *The soundscape methodology for long-term bird monitoring: A Mediterranean Europe case-study.* Ecological Informatics, 2011. **6**(6): p. 354-363.
12. Towsey, M., *Technical Report: The calculation of acoustic indices to characterize acoustic recordings of the environment. Brisbane: Queensland University of Technology. Australia.* 2012b.
13. Towsey, M., et al., *Visualization of Long-duration Acoustic Recordings of the Environment.* Procedia Computer Science, 2014. **29**: p. 703-712.
14. Hall, M., et al., *The WEKA data mining software: an update.* ACM SIGKDD Explorations Newsletter, 2009. **11**(1): p. 10-18.
15. Quinlan, J.R. *Learning with continuous classes*. in *Proceedings of the 5th Australian joint Conference on Artificial Intelligence*. 1992. Singapore.
16. Wang, Y. and I.H. Witten. *Inducing model trees for continuous classes*. in *Proceedings of the Ninth European Conference on Machine Learning*. 1997.