Automated acoustic identification of beetle larvae in imported goods using time domain analysis

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The detection of insect pests in imported goods is of considerable economic importance and the automation of this process is becoming more viable both technologically and financially. As a result, the Department for Environment, Food and Rural Affairs in the UK has funded a research project to develop instrumentation facilitating real-time acoustic detection of the feeding activity of insect larvae inside imported goods, such as timber. The instrumentation will also be capable of species-level identification. Previous work at York has shown that detection of beetle larvae in wood is possible using low cost piezoelectric sensors.

The project described here extends this work by investigating a number of signal analysis methods for robust detection of biting events, including fractal dimension analysis.

1 Introduction

The ability to detect insect pests in internationally traded goods is essential from both an environmental and economic point of view. On average between 2002 and 2006 13.2 Million cubic metres of wood was imported and 1.63 Million exported from the United Kingdom each year with a combined value of approximately £2.2 Billion [1]. This presents a considerable risk that unwanted species may be transported to the UK within the wood. The potential economic impact of an outbreak far outweighs the cost of monitoring. In the US, the potential impact of the introduction of the Asian Longhorned Beetle (*Anoplophora glabripennis*), a species native to Southeast Asia, was estimated at $669 billion [2].

In many cases, physical inspection of timber and trees is not feasible and a non-invasive method of detection is required. Acoustic detection is one such method which has been widely used commercially and in research for applications such as species identification [3] and behavioural monitoring [4].

The acoustic detection of insect larvae in timber is by no means new and has been performed as early as 1936 [5]. As technology has advanced, automated acoustic identification has become feasible [6].

This paper concentrates on the development of a robust automated real-time detection system for beetle larvae in wood.

2 Overview of system

2.1 Sensors

Piezoelectric transducers enclosed in plastic casing are used as vibration sensors for the system. These are then strapped around, or where possible, screwed into the wood or tree trunk under investigation.

2.2 Detection

Audio from the sensor(s) is recorded into a buffer from which bites are detected and passed on to the species classifier. The detection, classification and output stages are currently implemented in a C# application running on an embedded x86 PC.

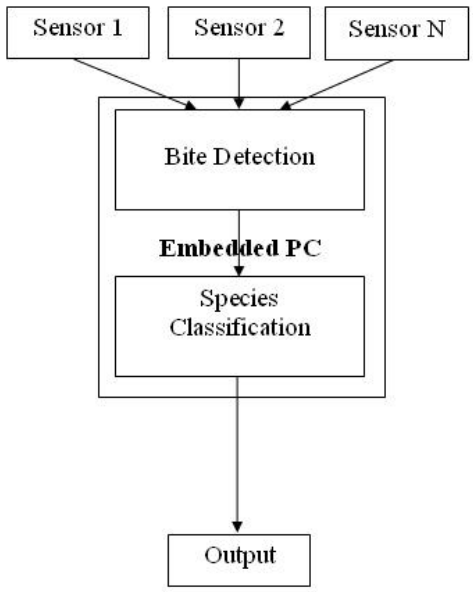

Figure 1: Block diagram of system

A comparison of two detection methods is presented in this paper.

2.3 Classification

The classification process analyses each bite and attempts to determine species of beetle which produced it. Currently a combination of Time Domain Signal Coding [3] and Artificial Neural Networks is used to classify bites by species.

2.4 Output

Primary output from the system is in the form of a visual display giving a real-time indication of the species detected since the system was installed. In addition to this are optional logs and audio data of detected bites in the event that manual identification or verification is required.

3 Ultra Short Time Energy Detection

A technique known as ultra-short-time energy detection has previously been used to detect both incidental [6] and non-incidental [7] insect sounds. The technique is based on the assumption that the acoustic event which is to be detected has a greater energy than the surrounding noise.

A full buffer of audio data is separated into M frames of a fixed length:

$$M = N/L \tag{1}$$

where N is the total number of samples and L is the frame length in samples.

The energy for each frame, $E_{use}(k)$ is then estimated using:

$$E_{use}(k) = \sum_{i=1}^{L} [x(kL+i)]^2, k = 0, ..., M-1 \tag{2}$$

where $E_{use}(k)$ is the estimated energy for frame k, L is group size, M is the number of frames and x is the input data.

4 Fractal Dimension Analysis

Fractal Dimension analysis is the calculation of the dimension of geometric shapes. Since a waveform can be thought of as a geometric shape, this analysis can be used to calculate a scalar value representing its complexity. This form of analysis is used for many applications, from the detection of earthquake phases [8] to the detection of cardiac function [9]. It is a powerful tool for acoustic event detection as the complexity of an acoustic event will differ from that of background noise.

Unlike conventional detection methods such as amplitude thresholding or energy detection (described above), fractal dimension is amplitude independent. Two waveforms with greatly differing amplitudes will have the same fractal dimension as long as they are composed of the same frequency components [10]. This is especially useful in environments where there is a low signal to noise ratio which would limit the usefulness of amplitude or energy thresholding.

As fractal dimension is difficult to calculate directly, several methods to estimate it have been developed.

4.1 Higuchi's Method

For a given time sequence $x(1), x(2), ..., x(N)$, k new time sequences may be constructed:

$$x_m^k = \left\{ x(m), x(m+k), ..., x(m + \left\lfloor \frac{N-m}{k} \right\rfloor k) \right\} \tag{3}$$

for m = 1, 2, ..., k.

For each of these time series, the average length can be calculated as:

$$L_m(k) = \frac{\sum_{i=1}^{\left\lfloor \frac{N-m}{k} \right\rfloor} |x(m+ik) - x(m+(i-1)k| \, (N-1)}{\left\lfloor \frac{N-m}{k} \right\rfloor k} \tag{4}$$

$L_m(k)$ is then averaged for all m to produce an array of means $L(k)$.

The fractal dimension can then be estimated as the slope of least-squares linear best fit of the curve $ln(L(k))$ versus $ln(1/k)$ [11].

4.2 Katz' Method

Katz' method estimates the fractal dimension as:

$$D = \frac{\log_{10}(n)}{\log_{10}(\frac{d}{L}) + \log_{10}(n)} \tag{5}$$

where D is fractal dimension, L is the total length of the curve, d is the diameter and n is the number of points on the curve.

Sevcik identified a flaw in Katz' method, showing that for any waveform Katz' equation (5) has the limit [12]:

$$D = \lim_{N\to\infty} \left[\frac{\log_{10}(n)}{\log_{10}(\frac{d}{L}) + \log_{10}(n)} \right] \tag{6}$$

For this reason, Kat'z algorithm was not investigated further.

4.3 Sevcik's Method

Sevcik's method estimates the fractal dimension using:

$$D = 1 + \frac{ln(L)}{ln(2*(N-1)} \tag{7}$$

where D is the estimated fractal dimension, L is the length of the curve mapped to a unit square and N is the number points on the curve [12].

4.4 Calculation Speed

For the purpose of detection, the accuracy of the fractal dimension estimation is not necessarily important. This is due to the detection system looking for a change in fractal dimension rather than an absolute value. As it is to be used in a real time system, computation time was the major factor in influencing which method to use.

Table (1) shows the time taken to calculate the fractal dimension of one minute of 16bit 44100Hz mono audio in Matlab 7.6 running on a Intel Pentium 4 2.2GHz machine with 1GB ram. The values are rounded to the nearest 100 milliseconds and are an average over 10 runs.

These results show that Sevcik's method offers a clear advantage over Higuchi's. The use of a compiled language such as C would increase the speed of both calculations but is unlikely to offer much improvement in calculating the least-squares linear best fit, which has the greatest impact on Higuchi's method.

Method	Frame Size (samples)	Calculation Time (s)
Higuchi	49	244.19
	98	113.1
	147	74.1
	245	50.6
Sevcik	49	30.56
	98	5.7
	147	1.6
	245	1.0

Table 1: Fractal Dimension Calculation Time

5 Comparison of detection methods

Given that Higuchi's method can slower than Sevcik's method by a factor of 50, further investigation deals with only the latter. From this point onwards fractal dimension values are estimated using Sevcik's method.

5.1 Frame Size

The frame size used has a major affect on the detection ability of both methods. A frame size which is too small will usually lead to detection of only a small segment of a bite whereas a frame size which is too large can lead to multiple bites being clustered together.

At a sampling rate of 44100Hz, a typical bite occupies around 200 samples. However the size varies from bite to bite as well as between different species. Additionally, the type of wood has an impact on the bite length.

Fig. (2) shows a typical *Hylotrupes bajulus* bite in pine.

Ideally, the frame size should be equal to the length of a bite and frame overlapping used to ensure the correct start position. Alternatively, the frame size can be set to some fraction of the average bite length if there is to be no frame overlapping.

Smaller frame sizes can improve detection but can lead to the detection of only parts of bites. This can be overcome by adding a predefined number of samples to the end of each detected bite.

The nature of the classification method means that bite detection does not need to be perfect. Small periods of noise at the beginning and end of a bite have a minimal impact on classification. This is especially useful in a real-time system as it negates the need to have overlapping frames which speeds up the detection process.

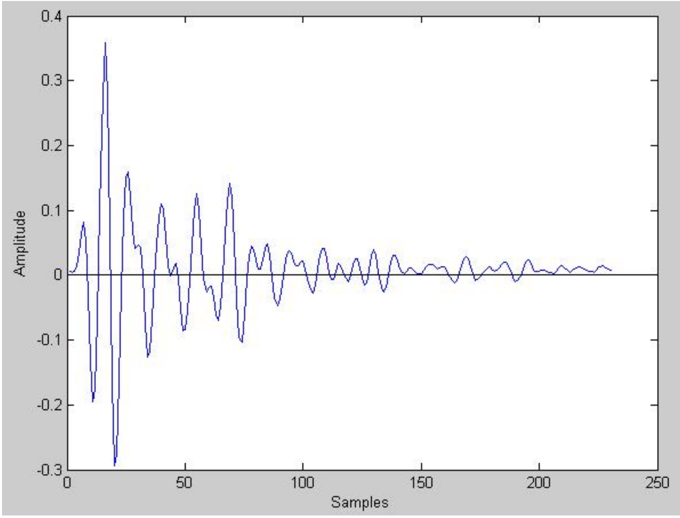

Figure 2: Single *Hylotrupes bajulus* Bite

5.2 Detection Threshold

The energy or fractal dimension values are normalised using Eq (8) in order to provide a measure of how much a frame differs from its surroundings. A simple threshold can then be applied to the output of the equation to determine whether a particular frame is an event.

$$\Delta_F = \frac{|C_F - \overline{C}|}{\sigma} \tag{8}$$

Where C_F is the energy or fractal dimension of the frame F, $\overline{C}$ is the mean energy or fractal dimension and σ is the standard deviation. Clearly, the larger the C_F value a bite's frame has, the easier it is to detect.

Additionally, horizontal thresholds can be applied to prevent single bites being detected as several bites in a row when using a small frame size.

6 Results

Fig. (3) and Fig. (4) show the potential ability to detect a *Hylotrupes bajulus* bite using frame lengths of 245 samples and 98 samples respectively.

The signal to noise ratio is calculated using peak voltages. The horizontal line in each graph represents the threshold level of 3. This figure is based upon the assumption that the noise will have a normal distribution and therefore 99.7% of noise frames will fall below this threshold.

Fractal Dimension appears to offer an advantage over Ultra-short-time energy detection of 5dB and 2dB for frame sizes of 245 and 98 respectively. Further investigation is required to show that this advantage still holds for other species of beetle.

Fig. (3) shows the average C_F values at different signal to noise ratios for 100 *Hylotrupes bajulus* bites embedded in 30 seconds of Gaussian noise each, using a frame size of 245 samples.

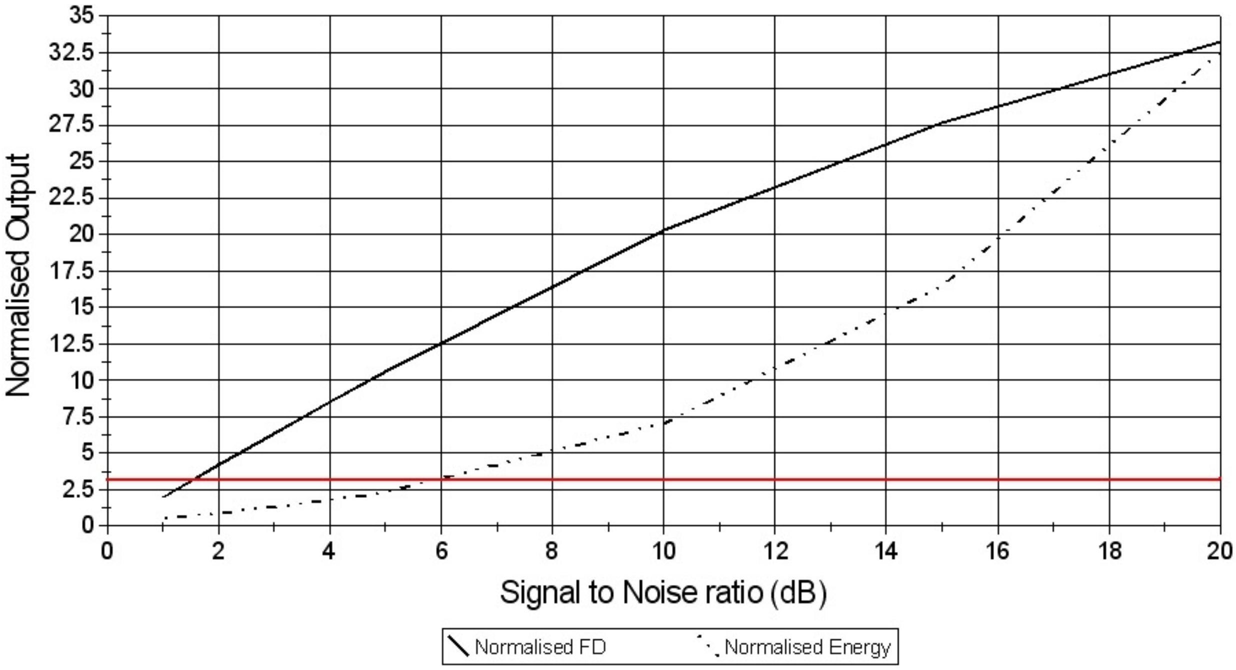

Figure 3: Comparison of Fractal Dimension and Ultra-short-time energy detection. (Frame Size = 245)

Fig. (4) shows the largest average C_F values for the same bites using a smaller frame size of 98 samples.

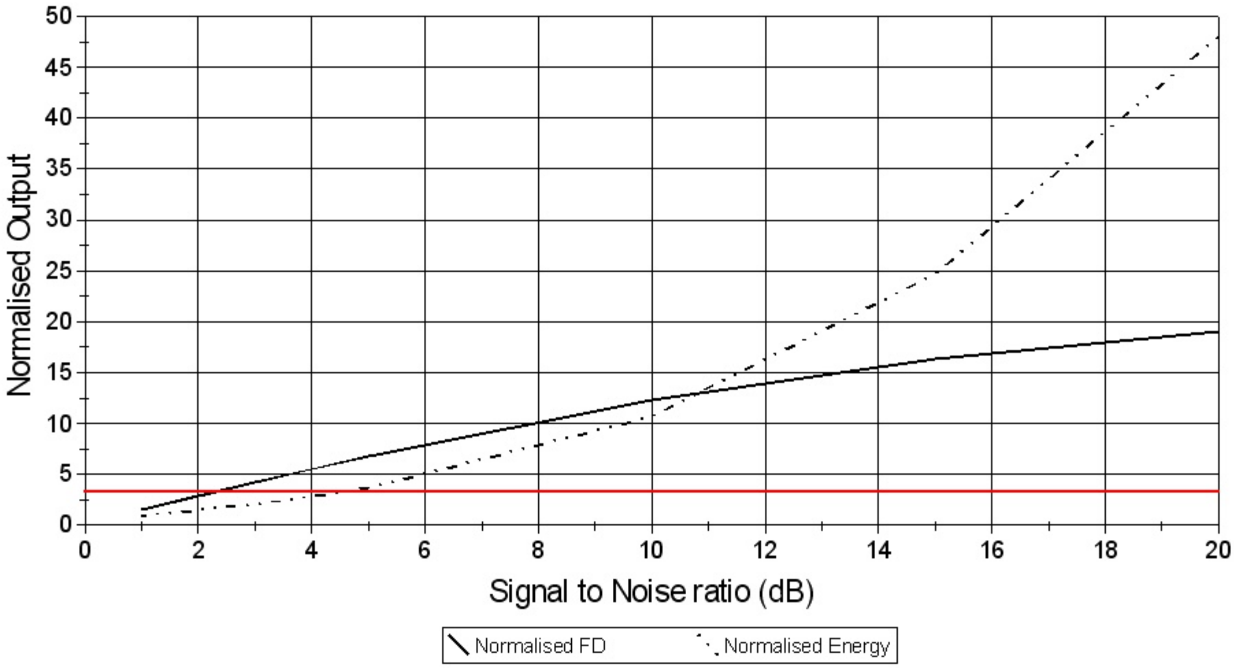

Figure 4: Comparison of Fractal Dimension and Ultra-short-time energy detection. (Frame Size = 98)

7 Conclusion and further work

Fractal dimension is a useful tool in event detection due to its relative insensitivity to amplitude. The results show that fractal dimension analysis offers a clear advantage over ultra-short-time energy detection in high noise environments. Further investigation will be carried out to determine the suitability of such bites for the purpose of species classification.

7.1 Classification using fractal dimension

Previously, species classification has been performed using a combination of time domain signal coding (TDSC) and artificial neural networks. Research into the possibility of using fractal dimension to classify bites by species is currently being conducted.

7.2 Sensors

Further research into the use of multiple wired and wireless sensors as inputs to the system will be carried out in the future.

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