Real-time Acoustic Identification of Invasive Wood-boring Beetles

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Abstract

Wood-boring beetles are a cause of significant economic and environmental cost across the world. A number of species which are not currently found in the United Kingdom are constantly at risk of being accidentally imported due to the volume of global trade in trees and timber. The species which are of particular concern are the Asian Longhorn (*Anoplophora glabripennis*), Citrus Longhorn (*A. chinensis*) and Emerald Ash Borer (*Agrilus planipennis*). The Food and Environment Research Agency's plant health inspectors currently manually inspect high risk material at the point of import. The development of methods which will enable them to increase the probability of detection of infestation in imported material are therefore highly sought after. This thesis describes research into improving acoustic larvae detection and species identification methods, and the development of a real-time system incorporating them.

The detection algorithm is based upon fractal dimension analysis and has been shown to outperform previously used short-time energy based detection. This is the first time such a detection method has been applied to the analysis of insect sourced sounds. The species identification method combines a time domain feature extraction technique based upon the relational tree representation of discrete waveforms and classification using artificial neural networks. Classification between two species, *A. glabripennis* and *H. bajulus*, can be performed with 92% accuracy using Multilayer Perceptron and 96.5% accuracy using Linear Vector Quantisation networks. Classification between three species can be performed with 88.8% accuracy using LVQ.

A real-time hand-held PC based system incorporating these methods has been developed and supplied to FERA for further testing. This system uses a combination of dual piezo-electric based USB connected sensors and custom written software which can be used to analyse live recordings of larvae in real-time or use previously recorded data.

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- National Plant Protection Organization, Netherlands

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Chapter 1

Introduction

In an age of mass international and intercontinental travel and wide-ranging global trade, animals, plants and other organisms are frequently transported between nations both intentionally and accidentally. Without suitable border control procedures the risk of accidentally introducing a non-native species into the United Kingdom is high. Some species, if introduced in this manner would become invasive; that is to say they would become established, potentially at the expense of other native species, and may pose a significant threat to the economy and environment.

Two commonly known examples of invasive species in the UK are the Grey Squirrel (*Sciurus carolinensis*) and the Japanese Knotweed (*Fallopia japonica*). The former causes environmental damage to trees by stripping bark whilst the latter causes economic damage as it weakens infrastructure such as roads and drains (Rayden and Savill, 2004), (Williams et al., 2010).

In the United Kingdom, the Department for Environment, Food and Rural Affairs (DEFRA) is the government department which has overall responsibility over the mitigation of such threats. One area of particular concern to DEFRA is the movement of plant material between countries. Imported living plants may harbour pathogens such as *Phytophthora ramorum*, which causes 'sudden oak death', and *Phytophthora kernoviae* which damages beech and rhododendron (FERA, 2011b), (FERA, 2011c). The threat is by no means limited to living plants; sawn timber, trees and even wooden packaging material may contain pests such as the Citrus Longhorn Beetle which will be discussed in detail in chapters 2 and 3 (FERA, 2010), (Haack et al., 2010).

The European Commission produces EU wide legislation regarding the import and export of plant material in the form of its Plant Health Directive (2000/29/EC) (European Commission, 2000). This includes lists of species for which import into the EU is forbidden or restricted, requiring specific measures such as kiln drying to have been undertaken prior to import. A statement on the opening page of the directive provides a justification for the measures: "Plant production yields are consistently reduced through the effects of harmful organisms. The protection of plants against such organisms is absolutely necessary not only to avoid reduced yields but also to increase agricultural productivity" (European Commission, 2000).

1.1 Governmental Organisations
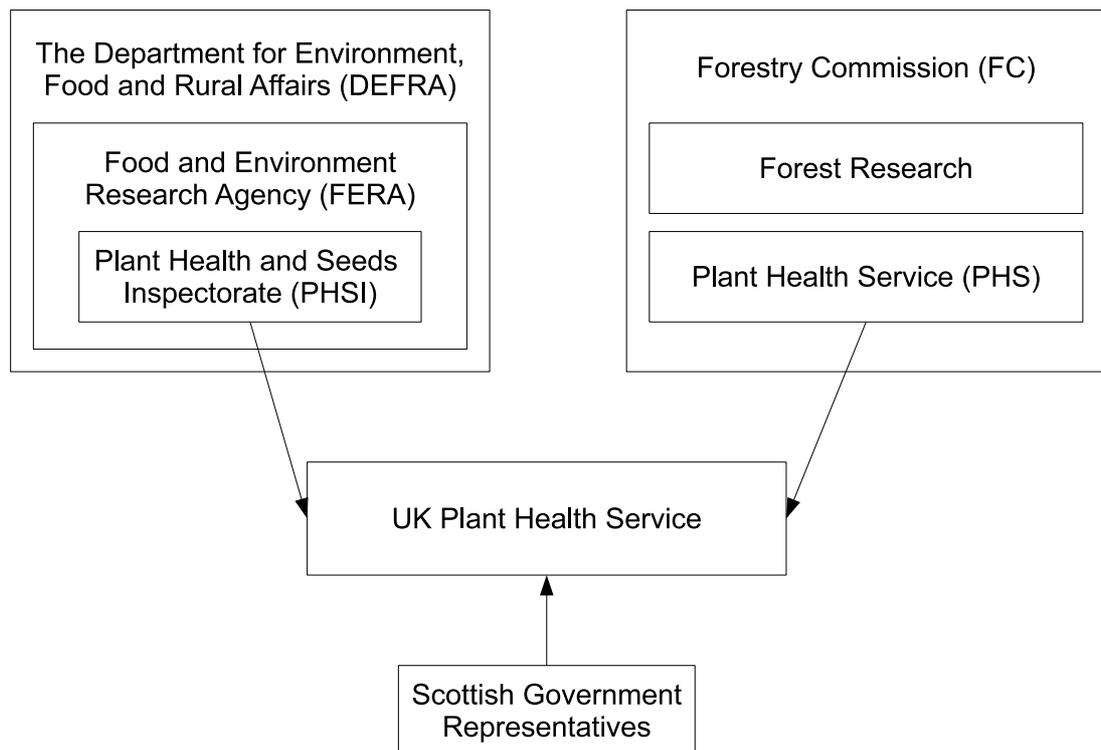
Figure 1.1: Relationship between relevant organisations and departments

A number of governmental organisations have responsibilities regarding invasive species and the import of plant material. As described in the previous section, DEFRA has overall

responsibility; however this is delegated to an executive agency, The Food and Environment Research Agency (FERA). The FERA website states that "Fera is responsible, on behalf of Defra, for implementing the plant health Regulations in England and Wales (on behalf of the Welsh Assembly Government). The Scottish Government is responsible for implementation in Scotland. Separate but similar arrangements apply in Northern Ireland." (FERA, 2011d).

A department of FERA, the Plant Health and Seeds Inspectorate (PHSI) has offices across the U.K. and is the body which is responsible for the inspection of plant material. This inspection is primarily performed manually and involves time-consuming visual inspection and destructive sampling of material. PHSI inspectors detect plant pests not only at points of entry to the U.K such as sea and airports but also at nurseries to issue plant passports for export and to monitor plants during post import growth.

The Forestry Commission is the organisation responsible for the management and protection of Britain's forests and woodland (Forestry Commission, 2011b). It has its own Plant Health Service (PHS) which cooperatives with PSHI to form the UK Plant Health Service. The Forestry Commission states the following: "The Forestry Commissions Plant Health Service (PHS) operates throughout Great Britain to prevent harmful pests entering GB and the European Union from overseas, and to eradicate or contain any that do become established." (Forestry Commission, 2011a).

An intergovernmental organisation, the European and Mediterranean Plant Protection Organization (EPPO), produces pan-European standards, publications and recommendations regarding plant health issues. Its stated objectives are "to protect plants, to develop international strategies against the introduction and spread of dangerous pests and to promote safe and effective control methods" (EPPO, 2011). EPPO maintains two lists of species which it recommends that its members regulate; the A1 list, which contains species not present within the EPPO region, and the A2 list, which contains species already present in the region (EPPO, 2010).

1.1.1 Relationship to DEFRA project PH0191

A previous DEFRA funded project, PH0191, with which the author had no involvement, is the predecessor to the current project. Part of the previous project involved feasibility study into the possible use of an automated acoustic system for the detection and recognition of insect pests. The overall aim of this project was to "to consider the feasibility of utilising novel acoustic detection technologies in the development of a tool for onsite detection and recognition of quarantined pests" (Farr, 2007).

The research proved that the automated acoustic detection and identification of beetle larvae is possible (to a limited extent). Classification of bites between two species, *Hylotrupes bajulus* and *Prionus coriarius* was performed to 97.8% accuracy (Farr, 2007) and prototype (non-realtime) acoustic larvae detection and identification system was produced during this project.

1.1.2 DEFRA Project PH0419

The research described in this thesis was undertaken as part of DEFRA Project PH0419 which was established as a result of the previous project. The proposal for this project states the following:

> "The purpose of this project is to aid the work of the Plant Health and Seeds Inspectors (PHSI) and Forestry Commission (FC) inspectors by improving their ablity to detect a range of statutory/quarantine pests using the acoustic methods initially investigated in a previous Plant Health Division funded project PH0191, which established proof of principle" (DEFRA, 2007)

In order to achieve this the proposal sets out two specific tasks:

1. **Refine the techniques which were developed in the earlier project (PH0191)**. This will include final consideration of optimal sensor selection and refinement of the species identification stage of the process.

2. **Produce two systems for use by PHSI and FC inspectors**
   a) The first system will perform real-time determination of the presence of quarantine species, and where required, an initial identification.

b) The second system will be capable of stand-alone operation and will act through a datalogging system, which can be used during transport of suspect material as well as at the point of import or at in-land points of destination.

At each stage of the system (sensors, audio capture, detection and identification) the approaches undertaken in the previous project will be investigated. Their suitability, with refinements where necessary, will be considered along with alternative approaches for implementation in the final real-time detection and identification system(s).

1.2 Novel Work

The novel work presented in this thesis is outlined below:

- The use of fractal dimension analysis as a method for the detection of larval activity sounds. This method outperforms short time energy detection for low amplitude events.

- The use of relational trees as a feature extraction technique to encode larval acoustic activity.

- The combination of relational tree features and artificial neural networks to acoustically identify wood-boring beetle larvae by species. Classification rates of 99% between two species and 90.4% between three species has been achieved.

- The development and implementation of a system capable of automated real-time beetle larvae detection and identification.

1.3 Thesis Structure

The chapters in this thesis are arranged to follow the stages of an automated acoustic detection and classification system. This begins by looking at the problem, invasive species, which are the reason for the development of the system. The sound source, beetle larvae, is then introduced in chapter 3. The automated detection process, which might be considered by some as classification between beetle species and noise, is covered in a separate

chapter to species identification. This is primarily because the methods use for bite detection are unrelated to those used for species identification due to the nature of the two tasks in this situation. Results are given within the relevant chapters rather than being listed separately. The system implementation chapter covers all stages of the detection and identification process. Figure 1.2 is intended to provide an overview of the relationship between chapters.

Chapter 2 introduces the concept of invasive species and covers their threat to both
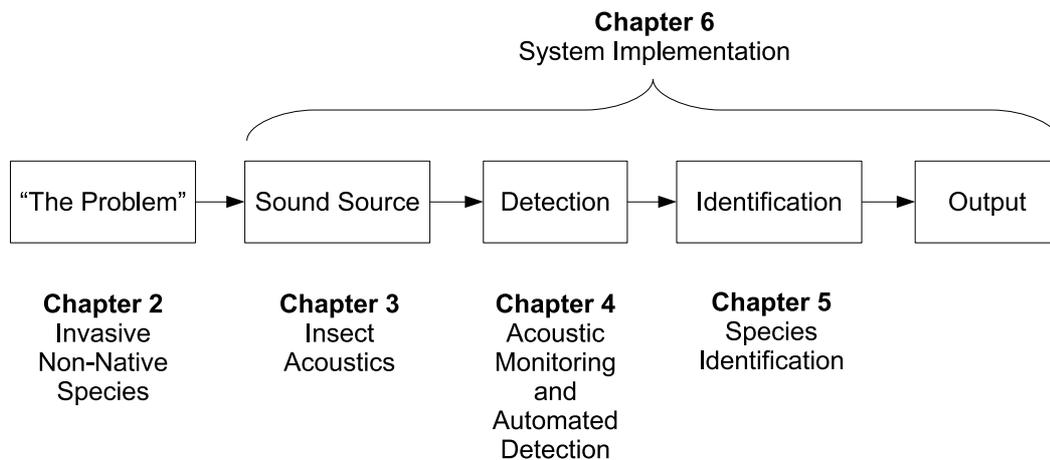
Figure 1.2: The stages of an identification system with chapter labels

the economy and the environment. It provides justification for this research by describing the scale of the problem posted by outbreaks of invasive beetle species and the limitations of the methods which are currently employed to detect their accidental introduction into the United Kingdom. Containment and eradication methods which have been used by governments to deal with outbreaks and infestations in other countries is also covered. The chapter concludes with case studies on two recent outbreaks of invasive wood-boring beetle species in the United States and Italy.

Chapter 3 covers the relationship between wood, insects and acoustics. The chapter begins by describing the process of acoustic transmission within materials and wood in particular, and looks at factors which may affect the transmission and ability to detect sounds at the surface of the wood. Sounds which may be sourced from the wood itself rather than any insects contained within are also considered.

Section 3.3 describes the categories of sounds which can be produced by insects along with the reasons for their production and the physical mechanisms which are used. The chapter then goes on to cover wood-boring beetle species in particular and the sounds which they produce during each stage of their life-cycles in relation to their suitability for use in an acoustic detection system. Sounds produced as a by-product of the feeding of larvae are detailed and factors which may affect their production are considered. The chapter concludes with case studies on two beetle species, the Asian Longhorn and Citrus Longhorn, which are of particular interest to this research.

Chapter 4 covers the methods used to detect the sound associated with the feeding of larvae from the surrounding noise. The chapter begins by considering the two categories of insect sound recording methods, substrate and airborne. The selection of optimum sensors for use in recording is then covered.

The computational methods which are currently used for acoustic event detection are then investigated before a new technique based upon Fractal Dimension analysis is introduced. A performance comparison between this method and Short Time Energy Detection is provided. Finally, the use of a secondary sensor for the reduction of false positive events is covered in addition to results for varied detection threshold levels.

Chapter 5 covers the methods used to identify the species of detected larval events. The chapter begins by detailing methods which have been used by others to detect and identify insects by their acoustic emissions.

A new identification method using relational tree structures in combination with an Artificial Neural Network (ANN) classifier is then introduced. Results are then provided for the classification between a number of species of beetle and between beetle and noise where a number of properties of the feature extraction method are varied.

Chapter 6 describes the implementation of the detection system as a whole. The chapter begins by considering the specified and implied requirements which DEFRA and PHSI have for the system. The methods and equipment used for acoustic recording of larvae

before the development of the automated system are then described. The hardware implementation is covered in section 6.3 and the use of dual channel USB attached sensors is described and justified. Section 6.4 covers the software implementation and aims to provide an overview of the system's capabilities in terms of input and output options. The relationship between the detection and identification stages in the software is described in addition to an overview of the threads which are used to allow the software to perform real-time analysis. The chapter concludes with a summary of the system which was delivered to PHSI to testing.

Chapter 7 provides conclusions on the research undertaken as part of this project. It also considers further work which could be undertaken as a result this research and in other areas which would allow the system described in this thesis to be developed further.

Chapter 2

Invasive Non-Native Species

This chapter serves as a justification for the research and is intended to give the reader an understanding of the scale of the problem which is faced by DEFRA and other related government agencies, and therefore the reasons for interest in the development of a system to assist in combating the threat. It introduces concept of invasive non-native species (INNS) along with their pathways, vectors, and impact on economy and environment.

The specific threat of wood-boring beetles to trees in the United Kingdom is discussed in section 2.2 which includes lists of high risk species. This section also includes estimates for the potential environmental and economic impact of outbreaks of invasive beetle species. Section 2.6 describes the methods which are currently used to prevent INNS from being imported in addition to control and eradication techniques which are used in pest outbreak situations.

The chapter concludes with case studies of outbreaks of two of the species of interest to this project, the Asian Longhorn and Citrus Longhorn Beetles, including a summary of the costs incurred and governmental responses.

2.1   Invasive Species

The term 'Invasive Species' has multiple definitions; in some cases it is used to describe only non-native species, in others it includes native species which are considered to have a negative impact on their surroundings. Similarly, the term is often used to describe any non-native species which is widespread, regardless of it's impact (Binggeli, 1994), (Colautti

and MacIsaac, 2004).

In the United Kingdom, an Invasive Non-Native Species (INNS) is defined by DEFRA as "any non-native animal or plant that has the ability to spread causing damage to the environment, the economy, our health and the way we live" (DEFRA, 2011); this term will be used for the remainder of this thesis. This chapter will also use the terms Pathway and Vector; the relationship between these along with examples are shown in Figure 2.1.
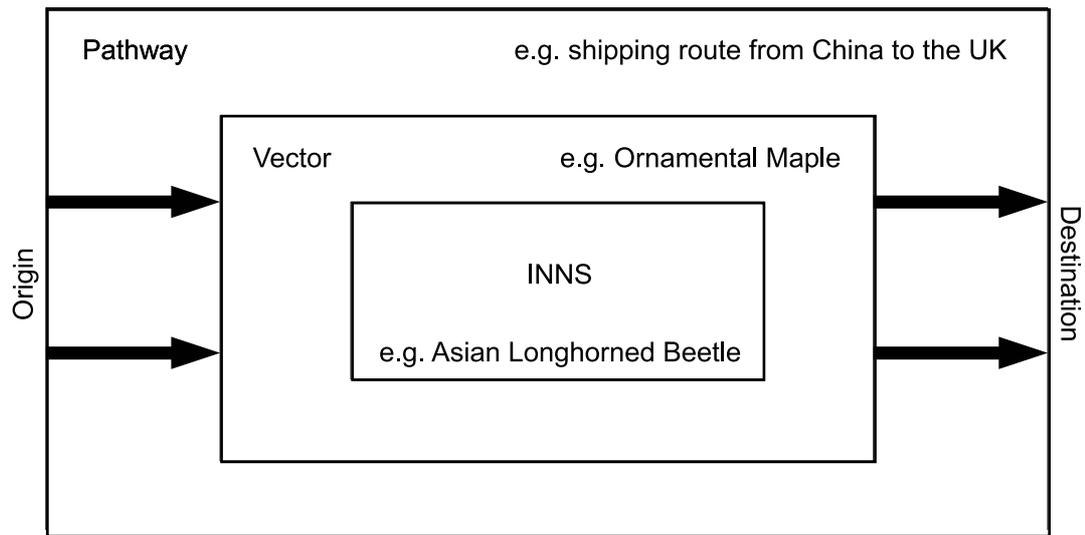
Figure 2.1: Invasive Non-Native Species - Causes, Pathways and Vectors

INNS pose a potential threat on a huge scale; it is estimated that over 11,000 non-native species have entered Europe (DAISIE, 2009) and approximately ten new non-native taxa become established across Europe each year (Hulme et al., 2009). Additionally, an estimated 21.4% of vascular plant species in Britain and Ireland are non-native (Vitousek et al., 1996).

2.1.1 Causes of invasions

Causes of invasions are either natural, accidental or intentional. Accidental and intentional invasions occur when human activity provides a suitable pathway and vector to carry the INNS. Pathways and Vectors are discussed in more detail in Sections 2.1.2 and 2.1.3 respectively. Accidental introductions are the by-product of the movement of persons or goods between different geographical areas. These may include, for example, the

importing of a non-native species to a zoo only for it to later escape and become invasive. The unintentional importing of a non-native species within internationally traded goods would also fall into this category. Accidental causes are generally related to human desire for internationally available goods or services.

Non-native species are sometimes introduced intentionally for economic or environmental reasons. For example, the American Mink (*Mustela vison*) was intentionally introduced to Europe in the 1920's for use in fur farming (Birnbaum, 2006). Escapes and intentional releases have resulted in the species becoming invasive (Bonesi and Palazon, 2007).

In Toronto, Canada, the Norway Maple (*Acer platanoides*) was introduced into public spaces as a replacement for North American Elm (*Ulmus americana*). It subsequently spread across the country and is now considered an invasive species (Foster and Sanberg, 2004). Another tree species, Saltcedar (*Tamarix* spp.), a perennial plant native to Eurasia, has become an invasive species in North America since it's introduction as an ornamental in the 19th century (Dudley and DeLoach, 2004). It is considered an undesirable species as it increases salt levels in the soil and displaces native vegetation (APHIS, 2005b). A leaf beetle, *Diorhabda elongata*, has successfully been introduced to some sites as a biological control agent (Dudley et al., 2006).

Stoats (*Mustela erminea*) were introduced to New Zealand in the 1880s to control the rabbit population (also an introduced species). However, the stoats predated on a native bird, the Brown Kiwi (*Apteryx mantelli*) to near extinction and are now considered invasive (King et al., 2007).

A list of common causes of invasions, categorised by whether they involve intentional or accidental introduction, is provided in Table 2.1.

2.1.2 Pathways

A pathway is the route from source to destination through which a species travels. These pathways may be natural or non-natural; common pathways for INNS are listed in Table 2.2.

Natural pathways are those which occur without human interference, for example cur-

Intentional Introductions		Accidental Introductions
Direct	Indirect	
Agriculture	Pets released into wild	Agricultural produce
Forestry	Zoo escapes	Nursery plants
Soil Improvements	Garden escapes	Cut Flowers
Food resources	Farming	Timber
Ornamental Plants	Research facilities	Seeds
Hunting	Aquaculture	Soil
Biological Control		Machinery and equipment
International aid		Packaging material
Fishery		Cargo
Conservation		Ballast Water
Sentimental Reasons		Ballast soil
		International planes
		Hull fouling
		Luggage

Table 2.1: Causes of invasions (Adapted from (Wittenberg and Cock, 2001) and (Burgiel et al., 2006))

rents in rivers, seas or the atmosphere (Ruiz and Carlton, 2003). The gulf stream is an example of a natural pathway as it has introduced tropical plants to the Isles of Scilly (Lousley, 1971). As natural pathways exist without the need for human interference there is little that can be done to prevent the introduction of INNS through them.

The majority of pathways for invasive species are non-natural, that is to say they are pathways created intentionally or unintentionally as a result of human activity. Generally speaking non-natural pathways are the result of travel, transport, trade or tourism and can consist of waterways, air-routes, railways or roads.

a) Travel and Tourism

International travel and tourism creates many potential pathways for INNS. In 1981, 11.5 million visits were made to the UK and 19 million visits to foreign countries were made by UK residents (Office for National Statistics, 2011). By 2009, these figures had increased

Pathways	
Natural	**Non-Natural**
Atmospheric Currents	Trade Related. e.g. Container ship routes
Oceanic Currents	Transport Related. e.g. Motorway corridors
Rivers	Tourism Related. e.g. Flight paths
Land Migration	Travel Related

Table 2.2: Common Pathways For INNS

to 29.9 million visits to the UK, and 58.6 million visits from the UK; increases of 260% and 196% respectively. Figures 2.2 and 2.3 show the breakdown of sources and destinations for these visits.
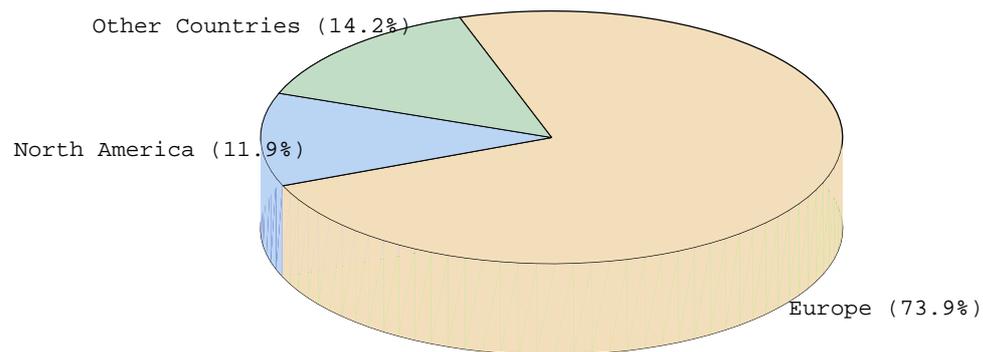
Figure 2.2: Travel from the UK in 2009

b) Trade and Transport

The economy of the United Kingdom is heavily reliant on international trade. The movement of internationally traded goods provides a significant pathway for invasive species. Figures 2.4 and 2.5 show the major sources and destinations of the United Kingdom's imports and exports. The major pathway for accidental invasion is internationally traded cargo (Ruiz and Carlton, 2003). In 2001, 2.2 million tonnes of freight was handled by UK airports and 566 million tonnes was handed by UK ports.
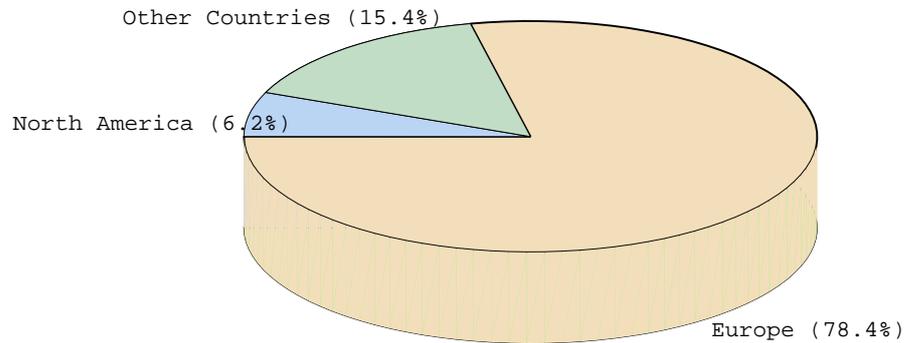
Figure 2.3: Travel to the UK in 2009

2.1.3 Vectors

A vector is the physical means by which an INNS is transported. A simple example being a person carrying a species from one location to another. Several vectors of INNS are related to international shipping. Ballast water, for example, is a significant vector for marine borne invasive species (Carlton and Geller, 1993); this is water which is stored within tanks on a ship to maintain its stability. This water is taken from the port from which the ship originates and can introduce non native species to the ship's destination if the ballast water is released. INNS can also be vectored by their physical attachment to the hulls of ships. The Zebra mussel (*Dreissena polymorphia*) was introduced to Ireland in the mid 1990s in this manner (Minchin et al., 2003).

The most significant shipping related vector is the movement of goods between countries. Several wood boring insects have been introduced by this vector. The European woodwasp (*Sirex noctilio*) was first discovered in New York in 2004, and in Ontario, Canada in 2005; most likely having been vectored by imported wood. (de Groot et al., 2006).

Whinam *et al.* conducted a study into the risk of expeditioners vectoring non-native species to subantarctic islands. Instrument cases and Velcro on clothing were identified
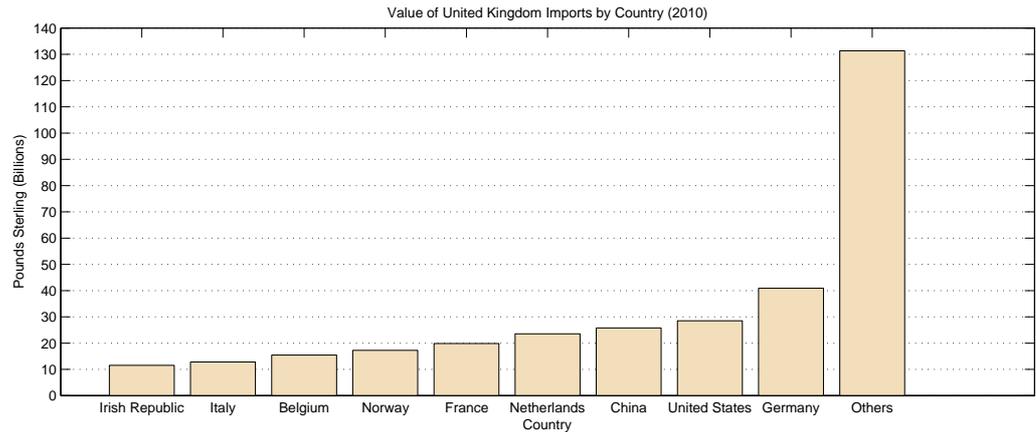
Figure 2.4: Value of Imports to the United Kingdom in 2010(Office for National Statistics, 2011)

Figure 2.5: Value of Exports from the United Kingdom in 2010(Office for National Statistics, 2011)

as high risk vectors. On an expedition in 2002, 44% of cargo items were found to be contaminated and 90 species were collected from the clothing of the 64 expeditioners (Whinam et al., 2005).

2.1.4 Economic Costs

These can be significant economic costs associated with the introduction of an invasive species. The economic costs of invasive species can be broken down into management costs, production losses and other costs. Management costs are those associated with the prevention, control or eradication of the INNS. This may include labour, research fund-

ing, equipment and publicity. Table 2.3 shows the areas of economic cost in addition to examples.

Direct Costs		Indirect Costs
Management Costs	**Opportunity Costs**	**Opportunity Costs**
Prevention, Eradication, Monitoring and Containment.	Production Losses e.g. decreased productivity	Impact on other sectors e.g. reduced employment
Labour, research funding, equipment and publicity	Increased disease damage.	Reduced availability and higher prices of vectors
Restoration Costs	Water shortage	Infrastructure damage

Table 2.3: Economic Costs of INNS (Adapted from (Emerton and Howard, 2008))

2.1.5 Environmental Impact

There are several ways in which an INNS can have a negative environmental impact. An INNS may successfully compete with a native species for resources, as the Grey squirrel (*Sciurus carolinensis*) does in the United Kingdom. INNS can also be responsible for lowering the biodiversity in their new habitat, for example the previously mentioned Saltcedar (see Section 2.1.1). Other INNS may attack species which are not used to having predators as has happened in North America where the Emerald Ash Borer is estimated to have destroyed more than 20 million trees in 10 years (Cappaert et al., 2005).

2.1.6 Other Issues

INNS can have a negative impact on human health, for example Smallpox (*Variola virus*) could be considered an INNS as it was introduced to the Americas by the Spanish in the 1500s (Glynn and Glynn, 2004). Some INNS are responsible for causing injuries and allergies, such as the Brown tree snake (*Boiga irregularis*) and the Gypsy moth (*Lymantria dispar*). The Oak Processionary moth (*Thaumetopoea processionea*) causes lepidopterism, a form of dertmatitis, in humans when they come in contact with the hairs of its larvae (Maier et al., 2003). Other species are themselves vectors of human diseases, for example the Raccoon Dog (*Nyctereutes procyonoides*) which is a vector for rabies (Pyek and Richardson, 2010).

2.1.7 Species Examples

2.1.7.1 Japanese Knotweed

The Japanese Knotweed (*Fallopia japonica*) is plant native to Japan, China and Korea which is classified as an invasive species in both the United Kingdom and other countries. It was introduced to the United Kingdom intentionally in the nineteenth century to be used in gardens (Williams et al., 2010). The plant causes environmental damage as it competes for resources with other plants. In the USA, Japanese Knotweed stem density has been shown to have a negative correlation with native plant species density, indicating that the knotweed can displace native species (Urgenson et al., 2009). It can cause damage to infrastructure such as tarmac and drains, and costs an estimated £5 million each year across the road network of Great Britain (Williams et al., 2010). The total costs of Japanese Knotweed to the British economy have been estimated as over £165 million annually (Williams et al., 2010).

2.1.7.2 Grey Squirrel

The Grey squirrel (*Sciurus carolinensis*) is a mammal native to North America. It was introduced to "various locations in Britain between 1876 and the 1920s" (Mayle et al., 2007). It strips bark, causing damage to a wide range of trees in the United Kingdom (Rayden and Savill, 2004).

There are also significant economic costs associated with its presence; a Forestry Commission document estimates that in Great Britain, Grey squirrel damage to beech, sycamore and oak will cause losses of around £10 million due to reduced crop value (Forestry Commission, 2006).

2.2 Wood-boring beetles and the Threat to Trees in the United Kingdom

The specific beetles which are considered a threat to the United Kingdom can be determined from various lists which are produced by relevant governmental organisations. The Forestry Commission maintains lists of pests which currently threaten trees in the United Kingdom and of threats not yet present (Forestry Commission, 2011c). The list includes

the five species of beetle which are shown in Table 2.4 below.

Species	Present in the UK
Emerald ash borer (*Agrilus planipennis*)	No
Citrus longhorn beetle (*Anoplophora chinensis*)	No
Great spruce bark beetle (*Dendroctonus micans*)	Yes
Oak pinhole borer (*Platypus cylindrus*)	Yes
Eight-toothed European spruce bark beetle (*Ips typographus*)	No

Table 2.4: Beetles which are a threat to trees in the United Kingdom

Species	EPPO List
City Longhorn Beetle (*Aeolesthes sarta*)	A2
Emerald Ash Borer (*Agrilus planipennis*)	A2
Citrus Longhorn Beetle (*Anoplophora chinensis*)	A2
Asian Longhorn Beetle (*Anoplophora glabripennis*)	A1
Ambrosia Beetle (*Megaplatypus mutatus*)	A2
Round-headed apple tree borer (*Saperda candida*)	A1
Fine-horned Spruce Borer (*Tetropium gracilicorne*)	A2
Altai Longhorn Beetle (*Xylotrechus altaicus*)	A2
Will Longhorn Beetle (*Xylotrechus namanganensis*)	A2

Table 2.5: Wood-boring beetles present in the EPPO A1 & A2 lists (EPPO, 2005)

Two species of beetle, the Asian Longhorned beetle (*Anoplophora glabripennis*) and the Khapra beetle (*Trogoderma granarium*), are listed amongst the 100 worst invasive species (Lowe et al., 2004) and the losses caused in the US by 43 alien insects between 1906 and 1991 have been estimated at over \$92.5 billion (OTA, 1993). The cost of the invasion in the USA since 1996 of Asian Longhorned Beetle has been over \$267 billion and has required the removal of 30,000 trees (USDA, 2007). The presence of beetles on this list and those produced by the Forestry Commission and EPPO show that invasive beetle species are considered to be a significant threat in the United Kingdom, Europe and worldwide.

2.3 Pathways and Vectors for Invasive Beetle Species

As discussed in Section 2.1.2, a pathway is route through which an INNS is introduced to a new area, whilst a vector is the physical means by which the INNS travels through the pathway. The major vectors for wood-boring beetles are trees and wood products. This project is primarily concerned with preventing the accidental invasion of alien beetle species through the importing these vectors. In the four years up to 2006 almost 15 million cubic metres of wood with an approximate value of £669 billion was either imported to or exported from the United Kingdom (Forestry Commission, 2007).

Data from the Office for National Statistics shows that in 2009, over 5.7 billion items in the category 'Wood and articles of wood; wood charcoal' were imported into the United Kingdom (Office for National Statistics, 2011). The source countries for these imports are shown in Figure 2.7. In the same time period over 297 million items in the category 'Live trees and other plants; bulbs, roots and the like; cut flowers and ornamental foliage' were imported. The source countries for these imports are shown in Figure 2.6. Figures 2.6 to 2.9 have been produced from data derived from the Office for National Statistics (Office for National Statistics, 2011).
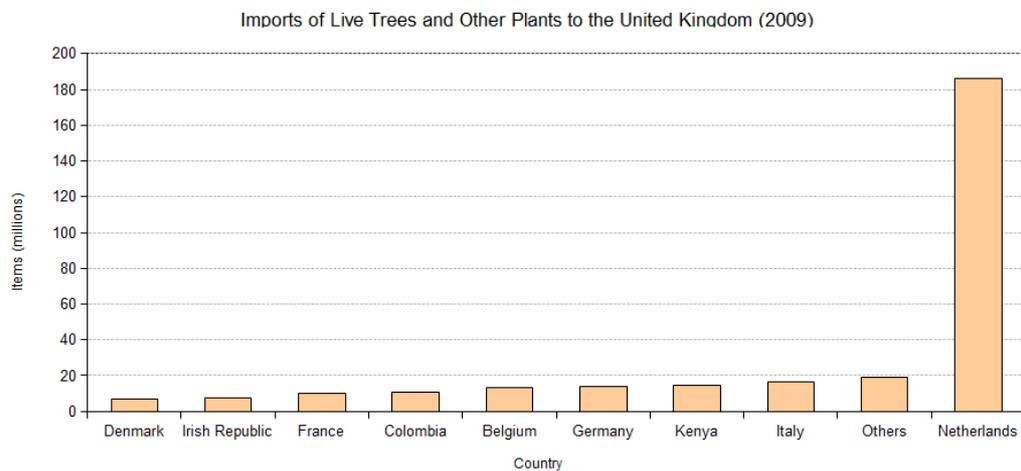
Figure 2.6: Imports of Live Trees and Plants to the United Kingdom (2009)
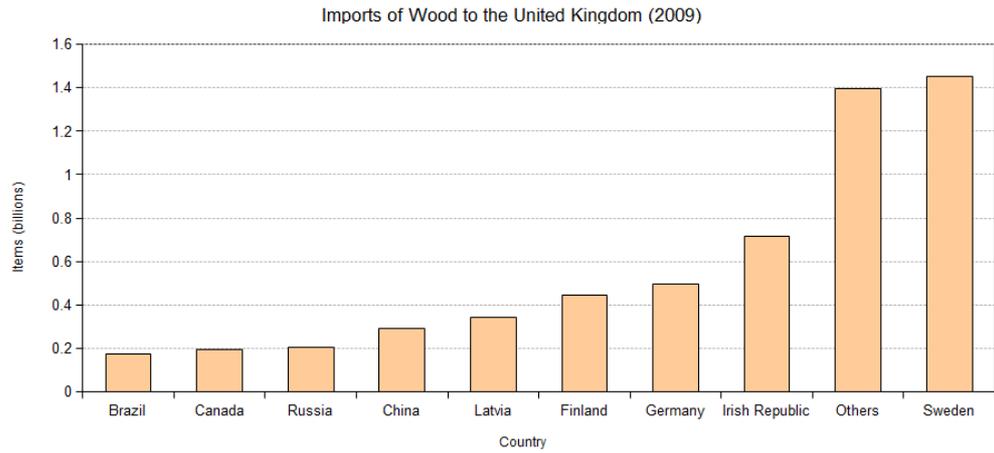
Figure 2.7: Imports of Wood to the United Kingdom (2009)
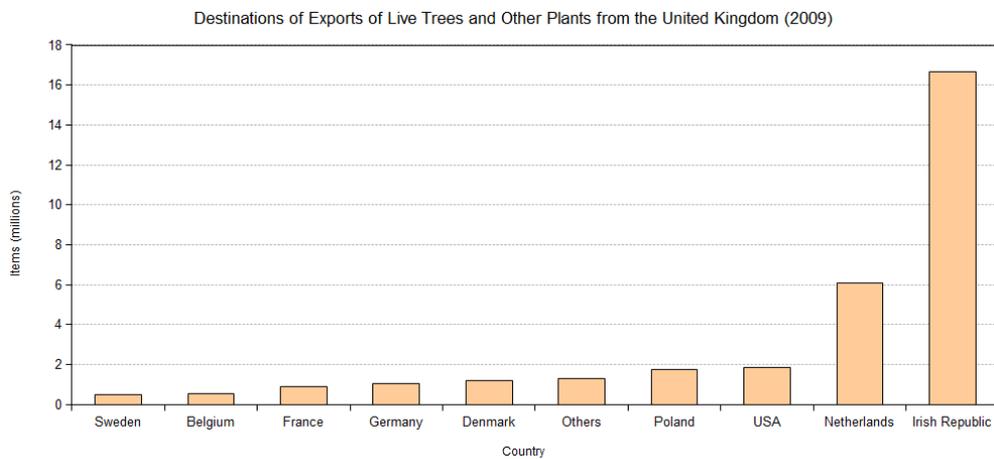
Figure 2.8: Exports of Live Trees and Plants from the United Kingdom (2009)
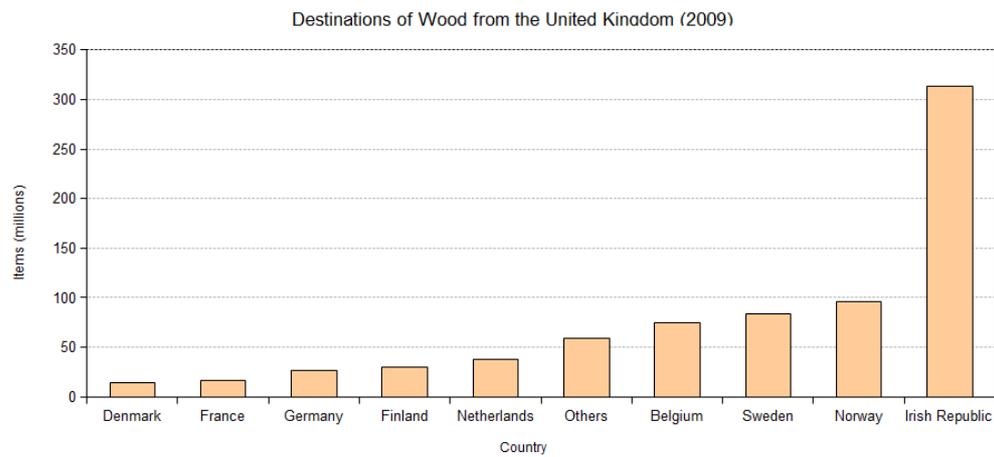
Figure 2.9: Exports of Wood from the United Kingdom (2009)

2.4 Economic Impact

The economic costs likely to be incurred due to an INNS have been discussed in Section 2.1.4. In this section the potential economic costs related to the introduction of invasive beetle species will be considered in more detail.

The Centre for Agricultural Bioscience International (CABI) produced a report for DEFRA, the Scottish government and the Welsh Assembly which provides estimates of the economic costs of invasive species (Williams et al., 2010). The report estimates that the INNS cost the United Kingdom £1.7 billion each year, of which £1 Billion is in the agriculture and horticulture sector. It also states that the greatest INNS costs are inflicted by plants.

The report also provides estimates which are specific to beetle species. Storage pests, the majority of which are non-native, are estimated to cost £6.5 million per year to control. A single species, the great bark spruce beetle (*Dendroctonus micans*) causes damages to forests and costs an estimated £32,000 per year in biological control and £130,840 per year in loss of yield (Williams et al., 2010).

Estimates are also provided on the likely costs of potential outbreaks for species which are not currently present. The report estimates that if the Asian Longhorn Beetle were to become established in the United Kingdom it could cost up to £1.3 billion to eradicate, based upon costs incurred in other countries. It estimates that if an infestation were left uncontrolled, the cost to the forestry industry would over £400 million based upon costs in the US (Williams et al., 2010).

2.5 Environmental Impact

The environmental impact of INNS can be difficult to quantify, particularly when trying to estimate the potential impact of the introduction of a species. The CABI report described in the previous section estimates that a single Asian Longhorn beetle infested tree could result in the destruction of 78.5ha of forest in order to control its spread (Williams et al., 2010).

Other estimates can be made by considering the environmental impact of beetle infestations in other countries. The Emerald Ash Borer infestation in the US, for example, is estimated to have destroyed more than 20 million trees in 10 years (Cappaert et al., 2005).

2.6 Prevention, Detection, Monitoring and Control

2.6.1 Prevention Methods

2.6.1.1 Legislation and Phytosanitary Certificates

Measures are routinely taken to prevent live larvae or adult beetles from being transported between countries. In the U.K, FERA is responsible for plant health matters. It separates imported plant material into three categories. These categories and their descriptions are shown in Table 2.6.

Category	Description
Prohibited	"Poses such a serious risk that import is only permitted under authority of a licence issued by FERA/WAG or the Forestry Commissioners. Includes many species of rooted plants and trees from outside Europe."
Controlled	"Normally requires a phytosanitary certificate issued by the plant protection service of the exporting country. Includes those cuttings, rooted plants and trees that are not prohibited, bulbs, most fruits, certain seeds and some cut flowers."
Unrestricted	"Presents little or no risk and is not subject to routine plant health controls. Includes nearly all flower seeds, some cut flowers and fruit and most vegetables for eating (except potatoes)."

Table 2.6: FERA Plant Material Categories. Adapted from (FERA, 2008).

Since material in the 'Prohibited' category is largely prevented from being imported, the most significant day to day risk is posed by imported material in the 'Controlled' category. As stated in Table 2.6, this material usually travels with a phytosanitory certificate which aims to prove that it has been inspected and meets the requirements for entry. FERA states that a phytosanitory certificate is "a statement that the plants or plant produce or products to which it relates have been officially inspected in the country of origin (or country of despatch), comply with statutory requirements for entry into the

EC, are free from certain serious pests and diseases, and are substantially free from other harmful organisms" (FERA, 2008).

2.6.1.2   Wood Treatment

Some sawn timber must be treated before it is allowed to be imported into the United Kingdom; this may involve kiln drying, heat treatment and bark removal. The specific requirements for the treatment of sawn timber are detailed in the Plant Health (Forestry) Order 2005.

The International Plant Protection Convention (IPPC) has produced a standard for the treatment of wood packaging material, "ISPM15 - Regulation of wood packaging material in international trade" (IPPC, 2009). This requires wood packaging material to be heat treated and stamped before export. The standard was incorporated into EU plant health legislation through EC council directive 2004/102/EC (European Commission, 2004).

2.6.2   Detection Methods used in the UK

Any material in the 'Controlled' category are inspected at the point of entry to the UK by plant health inspectors. Material in the 'Unrestricted' category may also be subject to random inspection (FERA, 2008). These inspections include a physical check for pests and diseases. For plants at risk of carrying invasive beetle species, the physical check includes visual inspection and manual destructive sampling.

2.6.2.1   Visual Inspection

In some cases a larval infestation can be detected through visual inspection alone. An inspector can look for visual indications of the possible presence of an infestation such as ovi-position holes, exit holes or frass around holes and at the base of trees. Such indications may not always be present or may be difficult to recognise; the risk of a false negative result is therefore high. This is particularly relevant in the case of an infested tree from which no adults have emerged. Another area of difficultly is in the inspection of timber products and pallets which can contain larvae but are more difficult to inspect than living trees since exit holes may be obscured and larvae may be located anywhere within the product.

2.6.2.2 Manual Destructive Sampling

Manual destructive sampling is the method currently employed by Plant Health Inspectors when investigating at risk plants entering the U.K. A proportion of samples are manually cut into small pieces and a visual inspection for signs of larval inspection is carried out. This is method is time consuming, expensive in terms of loss of commodity, and has a risk of human-error. There are some circumstances where destructive sampling is not always a viable option, for example where an individual high value plant is being transported.

2.6.3 Other Detection Methods

2.6.3.1 X Ray

Attempts have been made to detect wood-boring larvae with the use of X-Rays. In his 1940 paper, Fisher details the varying degrees of sucess in detection of a number of larvae using this method (Fisher, 1940). The wood samples used varied in thickness from $\frac{3}{16}$ inches (0.48cm) to $2\frac{1}{4}$ inches (5.71cm). The equipment used and small wood sample sizes required meant that this method could be of little use outside the laboratory environment.

X rays have been used numerous times to detect larvae inside grain (Schatzki et al., 1993), (Keagy and Schatzki, 1991). In their 2004 paper, Karunakaran *et al.* show that a combination of X ray and neural network based classification can be used to detect *Rhyzopertha dominica* with 99% success (Karunakaran et al., 2004). It is highly unlikely that such a technique could be adapted for the purpose of detecting larvae within wood due to the lack of portability of equipment used and the physical size difference between wheat kernels and standing trees. The author is not aware of any publications detailing the successful detection of wood boring larvae in standing trees using X ray methods.

2.6.3.2 Sniffer Dogs

Sniffer dogs have been successfully used to detect a number of insects including Gypsy moths (*Lymantria dispar*) (Wallner and Ellis, 1976), bed bugs (*Cimex lectularius*) (Pfiester et al., 2008) and screwworms (*Cochliomyia hominivorax*) (Welch, 1990).

Welch trained a German wirehaired pointer (*Canis familiaris*) to look for screwworms. An overall success rate of 99.7% was achieved, with a success rate of 94.7% for screwworm

infested animals. 8 months of training was required before the dog was able to detect screwworm pupae.

Pfiester *et al.* trained dogs to detect bed bugs and bed bug eggs. A 98% success rate in locating live bed bugs in a hotel room environment was achieved.

Recently there have been attempts to detect Bark Beetles using sniffer dogs (Feicht, 2006). It is unclear to the author as to whether this research is still ongoing.

2.6.3.3 Acoustic Detection

It has been known for several decades that, in certain conditions, wood-boring larvae can be detected acoustically. One of the earliest recorded methods of acoustic detection of larvae in timber used a variety of microphones as the sensor (Colebrook, 1937). This method required the wood under observation to be enclosed in a sound-proof container. Whilst no automated detection or analysis was performed in this experiment it demonstrated that larvae biting within timber does produce a detectable sound at the timber's surface. A similar approach was applied to listen for larvae in the timber of buildings (Schwarz et al., 1935). This demonstrated that acoustic detection can be used to detect larvae in a noisy environment.

Over the past 15 years interest in automated acoustic detection has grown and a number of methods have been investigated. These include the use of ultrasound (Fleming et al., 2005), piezo-electric and bi-morph sensors (Farr, 2007) and accelerometers (Mankin et al., 2004) in combination with various signal processing techniques to provide automated detection. Acoustic monitoring in general and automated detection using acoustics will be discussed in greater detail Chapter 4.

2.6.4 Eradication and Control Methods

Although the ideal situation is to have detected and prevented any invasive species from entering the country and therefore preventing any outbreaks, this is not always possible. A number of eradication and control methods have been used on established outbreaks.

2.6.4.1 Host Destruction

As the title suggests this involves the destruction of host trees, usually limited to high risk species over a defined area around an outbreak site. This method is expensive both environmentally and economically not only due to the cost of removal but also the cost of purchasing and planting replacement trees.

2.6.4.2 Biological and Microbial Control

There have been a small number of publications on the use of fungi to control beetle populations. Higuchi *et al.* investigated the use of a fungus, *Beauveria brongniartii*, as a control agent for yellow spotted longicorn beetle (*Psacothea hilaris Pascoe*) and determined through field trials on tangerine crops that it was capable of killing adult beetles and preventing further infestation (Higuchi et al., 1997).

Hajek *et al.* conducted studies into the effectiveness of a number of species of fungi against the Asian longhorned beetle (Hajek et al., 2007). Infection with *Metarhizium anisoplia F52* was found to cause adult female beetles to produce fewer eggs before their death.

Herard *et al.* studied the egg parasitoid *Aprostocetus anoplophorae* as a potential biological control agent for Asian and Citrus Longhorn beetles (Herard et al., 2004), (Delvare et al., 2004). The study concluded that the parasitoid has potential to be used as a control agent for Citrus Longhorn but not Asian Longhorn beetles.

2.6.5 Outbreak Monitoring

2.6.5.1 Sentinel Trees

Sentinel trees are used in some infestation sites to help monitor the spread of the invading species. Trees which are known hosts of the invader are placed around the infestation in order to attract it to them as it spreads.

This technique was used to monitor the spread of *Anoplophora chinensis* in Lombardia, Italy. Sentinel trees were placed within a buffer zone extending 1-2km from the infested

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area and visually inspected twice per year for signs of infestation (Maspero et al., 2007).

Field studies have shown that both sexes of *Anoplophora glabripennis* are highly attracted to *Acer pictum subsp. mono* (Smith et al., 2009). A second species, sycamore maple (*A. pseudoplatanus*) has been used as a sentinel tree during *Anoplophora glabripennis* eradication efforts in Italy (Herard et al., 2009a).

2.6.5.2 Acoustic Monitoring

A detection system capable of automatically identifying beetle larvae could potentially be used to assist in outbreak monitoring. Such a system could be combined with the sentinel tree approach to more efficiently monitor the spread of the outbreak. The use of a wireless sensor network combined with an automated acoustic detection system opens up the possibility of a fully automated outbreak monitoring technique requiring little or no human intervention.

2.7 Outbreak Case Studies

2.7.1 *Anoplophora glabripennis* outbreaks in the US

The Asian Longhorned beetle is indigenous to China and Southeast Asia. Over 40 species of host tree have been identified (Yang et al., 1995), but the major hosts are *Populus nigra*, *Populus deltoides*, *Poplulus x canadensis*, *Populus dakhuanensis* and *Salix* spp. (EPPO, 2004). The presence of an infestation weakens the host tree, and on leaving, adults produce large exit holes which may ooze sap (APHIS, 2005a). The Asian Longhorned beetle is discussed in greater detail in Section 3.7 of Chapter 3.

Asian Longhorned beetle was first discovered in the US in 1996, in New York City (Haack et al., 1997). Further outbreaks have since been discovered in Chicago, Illinois, in 1998 (Poland et al., 1998) and Jersey City, New Jersey, in 2002 (Haack, 2003).

U.S. Department of Agriculture (USDA) officials have determined that the vector of the initial outbreak was solid wood packing material (SWPM) from China (APHIS, 2005a). The initial response was to introduce a federal quarantine to regulate the movement of at risk host material and to introduce an eradication program to rid the US of infested trees

(Haack, 2003). The USDA believes that the most effective method of eradication is to cut and chip or burn infested trees (APHIS, 2005a). Wang *et al.* conducted a study showing that chipping is sufficient for killing nearly all larvae (Wang et al., 2000).

As of 2003, the infestations had required the removal of over 30,000 trees and cost more than $269 million. Potential losses of over $41 billion were estimated should the infestations spread beyond the initial three quarantined areas (APHIS, 2007).

2.7.2 *Anoplophora chinensis* outbreak in Lombardia, Italy

The Citrus Longhorned beetle is indigenous to China and Korea. The EU commission considers 17 species to be the most significant hosts (FERA, 2010). These include *Acer* spp. (maple), *Salix* spp. (willow) and *Populus* spp. (poplar). Citrus Longhorned beetle causes damage in a very similar way to Asian Longhorned beetle. Infested trees are left more susceptible to diseases and leaf damage can be caused by the feeding of adults (FERA, 2010).

Citrus Longhorned beetle was first discovered in Lombardy, Italy in 2000 (Colombo and Limonta, 2001). As of 2007, infestations had been identified in 30 municipalities around Milan (Maspero et al., 2007). The European and Mediterranean Plant Protection Organisation (EPPO) believes the vector for the infestations to be ornamental trees imported from East Asia (Herard et al., 2009b).

The governmental response to the outbreak was to initiate eradication and monitoring programmes. The monitoring relied heavily on the use of sentinel trees (as described in Section 2.6.5.1) which were planted within a buffer zone around the outbreak area. The buffer zone extended 1-2km outside the known infested area.

Between 2001 and June 2007, 3098 trees had been destroyed as part of the eradication process (Maspero et al., 2007).

2.8 Summary

This chapter has introduced the concept of INNS and the related terms 'Pathways' and 'Vectors'. The common causes of invasion, categorised into natural, accidental or intentional have been discussed. The cost of invasive species with regards to their impact on the environment and economy has been discussed. The increasing risk to the U.K of invasion of invasive species in general due to its levels of international trade, transport and tourism has been considered.

The risk posed by wood-boring beetle species has been described in detail and the economic and environmental costs associated with infestations have been considered. An overview of the different methods which have been used to prevent, detect, monitor and control invasive beetle infestations has been given and the use of automated acoustic detection as a preventative technique has been introduced.

Finally, case studies of outbreaks of two of the species of interest to this project (*Anoplophora glabripennis*) and *Anoplophora chinensis* in the US and Italy have been produced.

Chapter 3

Insect Acoustics

This chapter covers the combination of larvae and host tree as a sound source, beginning by detailing how sound waves are transmitted through different materials and the properties which can affect transmission. Trees and timber as media for sound transmission and as sound sources are then considered and the basic structure of trees is outlined.

The next area to be covered is the types of sound which are produced by insects and the categories into which they are placed based upon the method by which they are produced and the purpose for their production.

The sound production of wood-boring beetles and in particular their larvae is then explained in relation to the acoustic detection task; this includes looking at the relationship between the behaviour and morphology of the larvae and the resulting sounds; and the possible impact of a number of properties of the host. Finally, detailed descriptions of the three beetle species which are of most interest to this research (*Anoplophora glabripennis, Anoplophora chinensis and Agrilus planipennis*) are given.

3.1   Sound Waves and Transmission

Sound is simply the transmission of vibration through the particles of a material. The principles remain the same whether the material may be solid, liquid, or gas. Sound is transmitted, or propagated, through a material by the transfer of energy between the particles that make up the material. The sound source causes particles to vibrate; this in turn causes neighbouring particles to vibrate and so on. Each time this vibration is

passed on a small amount of energy is lost. The term used for the loss of energy through transmission is attenuation.

Figure 3.1 gives a basic overview of sound transmission. The upper half of the figure shows the sound wave's impact on the pressure of particles as it progresses away from the source. The darker bands represent high pressure and the lighter bands low pressure. The lower half of the figure shows the perception of the sound received over a period of time by the observer. The period of the sound wave, also known as the wavelength is the time between successive periods of peak or minimum pressure.
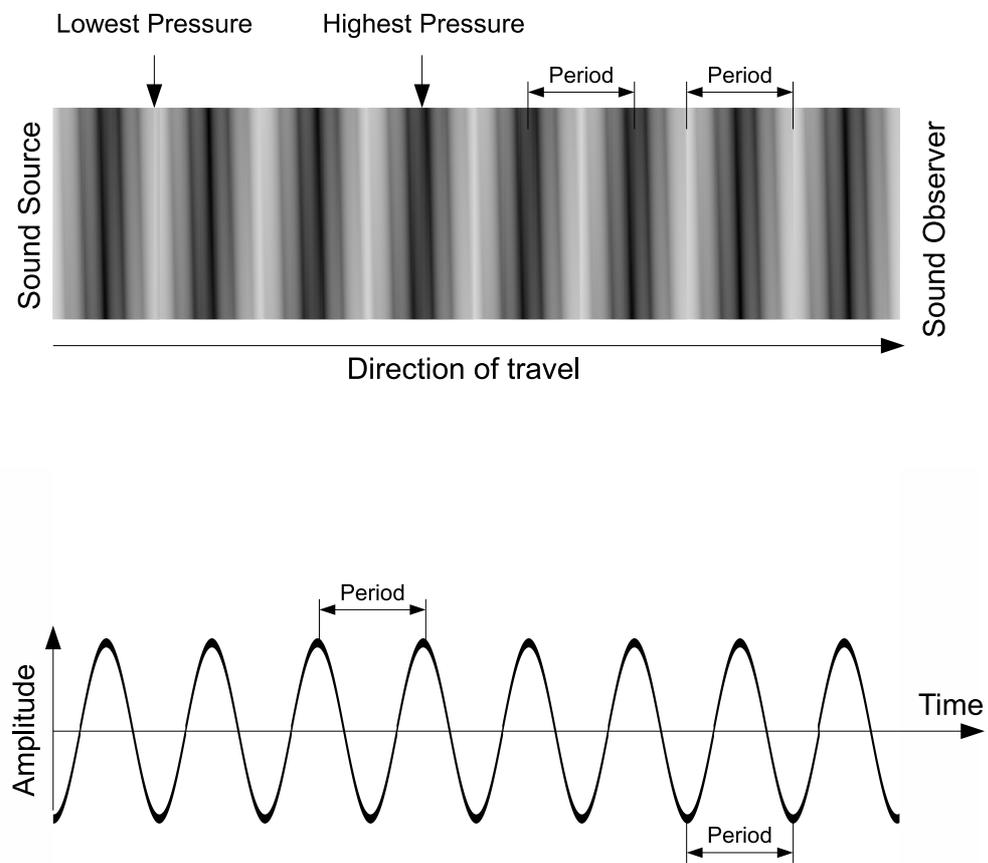
Figure 3.1: Sound transmission

3.2   Sound Transmission in Wood

For the purposes of detecting wood-boring larvae, the sound source can be considered to be the combination of larvae and host material (the tree, plant or wood). The physical properties of the host material will affect both the ability to detect the presence of any larvae, and the exact nature of sounds detected.

The composition of a material affects sound travelling through it in two significant ways: attenuation and velocity. Attenuation is the rate at which energy is lost by the sound wave as it passes through the material; velocity being the speed at which a wave travels through the material. Density primarily affects the velocity of the wave, with sound being transmitted faster in less dense materials. This is because a particle of lower mass can be displaced further than a particle of greater mass given the same amount of force exerted on it. The density of wood clearly varies between species but is also dependent on other factors. In dried conditions, the density of Oak can be between 1 and 3 times that of Canadian Pine and 5 times that of Balsa wood (simetric, 2009).

3.2.1   Factors influencing the acoustic properties of wood

Even after taking into account variations between difference species, the acoustic proper- ties of wood can vary. Cut wood or packing materials are more likely to vary in moisture content than standing trees; this can affect the both the attenuation and velocity of sound within wood. As moisture content increases, wood density increases leading to a decrease in sound velocity (Unterwieser and Schickhofer, 2011).

Another property to consider is the degree of decay; like moisture content this can change the density of the wood. It does not occur evenly meaning that areas of very low density may occur within in otherwise un-decayed wood. The level of decay can affect the ease of attachment of sensors and the quality of acoustic coupling attained once sensors are attached.

Figure 3.2 shows the cross-section of a tree trunk with different regions labelled. It can be seen from this diagram that a tree is not a simple continous solid with unchanging structure, but a complex one with several layers each with differing density and elasticity. The layer in which a sound is produced may have a significant impact on how well it is
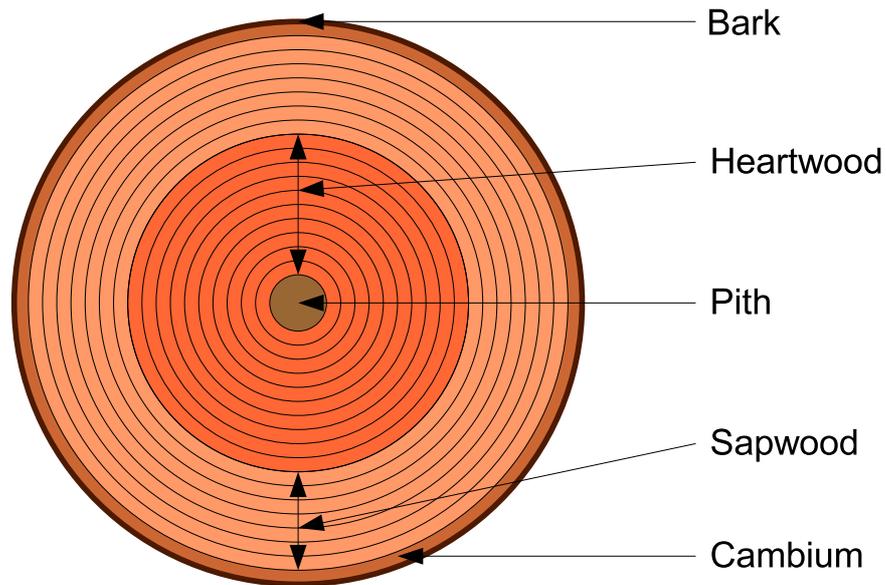
Figure 3.2: Cross-section of a tree

transmitted to the tree's surface.

Finally, the grain within wood produces a variation in density meaning that the speed of sound transmission is related to the angle of the wave to the grain (Ross, 1999). In the case of live trees there is nothing that can be done to adjust the angle of the sensor with respect to the grain, however in cut wood there may be advantages in placing sensors at particular angles.

3.2.2 Wood Sourced Acoustic Emissions (AE)

In addition to transmitting sounds, in certain situations trees and wood may also be a sound source. One cause of wood sourced AE is stress and fracture. As is the case with other solid materials, as pressure is exerted on wood fibres they can break producing vibrations which travel through the tree or timber. Several studies have used these emissions in the stress testing of timber and as an indicator of decay (Raczkowski et al., 1999), (Antal, 2004), (Ayarkwa, 2010).

Some sounds are produced in standing trees but not in cut wood, by virtue of them consisting of living material. An example of this is sound produced due to cavitation, which is defined as "the formation of one or more pockets of gas (or cavities) in a liquid" (Apfel, 1981). This process occurs within the fibres of trees as low sap pressure causes xylem walls to break and become filled with air (Bucur, 2006). The emissions produced by cavitation can be detected using ultra-sonic sensors at the surface of the wood (Borghetti et al., 1989), (Raschi et al., 1989).

3.3 Insects and Acoustics

Insects produce a wide range of sounds for a variety of purposes and for no purpose at all; these can be divided into two distinct categories. Incidental sounds are those produced as a by-product of some other action which the insect performs, such as feeding. Non-incidental is used to categorise any sound intentionally produced, for example in communication. Figure 3.3 shows most common insect sounds categorised by their type. For non-incidental sounds the reason for producing the sound is given, for example to attract a mate; for incidental sounds the action for which the sound is a by-product is given, for example feeding.

Non-incidental sounds are most commonly produced for some form of communication with other members of the same species, Cicadas, for example produce a sound to attract others (Alexander and Moore, 1958). Communication sounds can be further categorised by the situation in which they are produced. Ewing lists the known categories as: calling, courtship, aggregation, aggression, copulation and disturbance (Ewing, 1984). Intentionally produced sounds are not limited to communication; recent studies have shown that Tiger Moths (*Bertholdia trigona*) use non-incidental sounds for self preservation by disrupting bat sonar (Corcoran et al., 2009).

The method of transmission of sounds by insects can be further categorised into two groups, substrate and airborne. Substrate in this context means the material which an insect is on or in, often a plant or tree as opposed to airborne in which sound is transmitted without the use of a solid medium. The means of production of these sounds may involve some form of physical interaction with the substrate such as striking. The means of sound transmission has implications on the methods which are used to detect them; this will be

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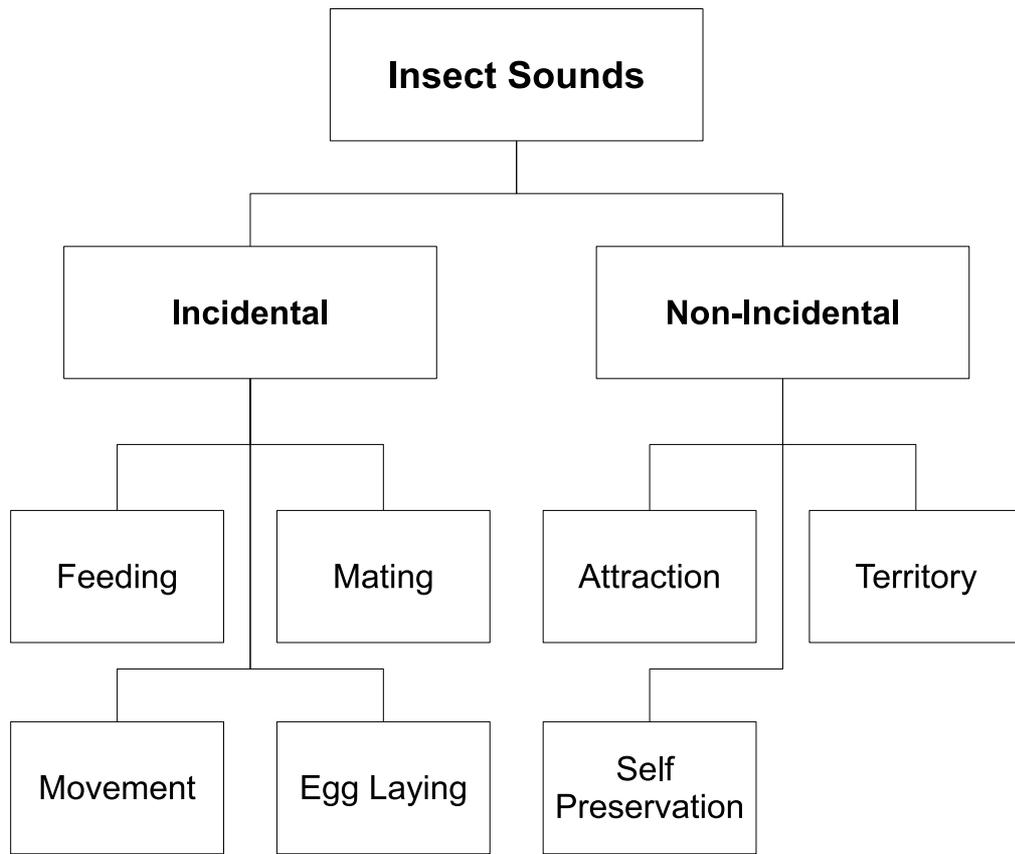
Figure 3.3: Categories of insect produced sounds

discussed in Chapter 4.

Sounds in both of these categories by be produced by a number of different physical mechanisms. In his 1957 paper, Alexander produced five categories for the mechanisms used by insects in sound production; these categories are summarised below (Alexander, 1957).

- Stridulation

  This is where sound is produced as one body part is rubbed against another. An example of this is species of Dung Beetle, *Aphodius ater*, which uses an organ on the abdomen to produce stridulation (Hirschberger, 2001). Hirschberger hypothesises that the sound produced is used by females to select mates since only the male of the species regularly stridulates.

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- Striking

  This is the striking of a part of the insect's body against the substrate or another area of the body. Various different body parts are used depending on the insect species; for example some male cockroaches use this mechanism by striking their abdomen (Bell et al., 2007). The Death Watch Beetle (*Xestobium rufovillosum*) performs a similar action by striking the head (Birch and Keenlyside, 1991).

- Vibration

  The vibration of a body part, such as the wings, can produce airborne sounds. All flying insects produce incidental sounds as the oscillation in their wings is transmitted to the surrounding air. The frequencies produced by the wings of most insects falls within the range 50Hz to 2kHz (Price, 1984); bees, for example, beat their wings at around 190Hz (Chapman, 1998). Butterflies and moths tend to beat their wings at a slower rate, producing sounds at frequencies as low as 8Hz (Corben, 1983).

- Tymbal vibration

  Some insects have drum-like membranes called tymbals which can be vibrated. A tymbal is a highly specialised body part which exists only for sound production; it's surface either has a number of ribs or is smooth and produces a clicking sound when caused to buckle by an associated muscle (Shaw and Carlson, 1979). Examples of insects which produced sounds using this mechanism include Moths and Cicada (Fullard and Heller, 1990), (Simmons and Young, 1978). Sounds produced by Cicadas using tymbals are in the range 4 - 7kHz (Gullan and Cranston, 2010), (Bennet-Clark, 1997), (Young and Bennet-Clark, 1995).

- Ejection of air or fluid

  Hissing or whistling sounds are produced as air or fluid is forced out of the body. The sound produced may be incidental, produced purely as a by-product rather than an intentional sound; some grasshoppers for example eject a jet of liquid as a defence mechanism (Hingston, 1927). In other insects sound is produced intentionally by

this method; the Madagascar hissing cockroach (*Gromphadorhina portentosa*) is one such example (Clark and Moore, 1995).

The range of frequencies which can be produced by different insects is wide, ranging from the infrasonic, such as that of butterfly wing beating, to ultrasonic, such as the stridulation of katydids (Corben, 1983), (F. Montrealegre-Z and Mason, 2006). Table 3.1 provides a summary of insect produced sounds and their frequency ranges.

Species	Sound Type	Frequency	Reference
Butterflies	Vibration	8 - 90 Hz	(Corben, 1983)
Death Watch Beetle	Striking	$\approx 11 Hz$	(White et al., 1993)
Bees	Vibration	$\approx 190 Hz$	(Chapman, 1998)
Tree Hoppers	Striking	$\approx 500 Hz$	(Cocroft, 1999)
Cicadas	Tymbal Vibration	4 - 7 kHz	(Gullan and Cranston, 2010), (Bennet-Clark, 1997)
Grasshoppers	Stridulation	up to 30 kHz	(von Helversen and von Helverson, 1998),(van Staaden and Rmer, 1997)
Bush Crickets	Stridulation	up to 129 kHz	(F. Montrealegre-Z and Mason, 2006)

Table 3.1: Frequencies of insect produced sounds

3.4 Wood Boring Beetles and Acoustics

Before considering the types of sound that may be produced by wood-boring beetles the lifecycles and behaviour of these insects should first be understood in order to determine how best to detect them. Figure 3.4 shows the lifecycle of a wood-boring beetle.

```
┌─────────────────────┐              ┌─────────────────────┐
│       Adult         │              │        Egg          │
│                     │  ─────────▶  │                     │
│  Flying             │              │  Laid on the surface │
│  Feeding            │              │                     │
│  Mating             │              │                     │
│  Egg laying         │              │                     │
└─────────────────────┘              └─────────────────────┘
         ▲                                     │
         │                                     ▼
┌─────────────────────┐              ┌─────────────────────┐
│       Pupa          │              │       Larva         │
│                     │              │                     │
│  Pupation occurs    │  ◀─────────  │  Feeding and        │
│  close to           │              │  tunnelling         │
│  the surface of     │              │  within the wood.   │
│  the wood.          │              │                     │
│                     │              │  Multiple distinct  │
│  After pupation     │              │  larval             │
│  adults             │              │  stages known as    │
│  emerge through     │              │  Instars.           │
│  exit               │              │                     │
│  holes on the       │              │                     │
│  surface of         │              │                     │
│  the wood.          │              │                     │
└─────────────────────┘              └─────────────────────┘
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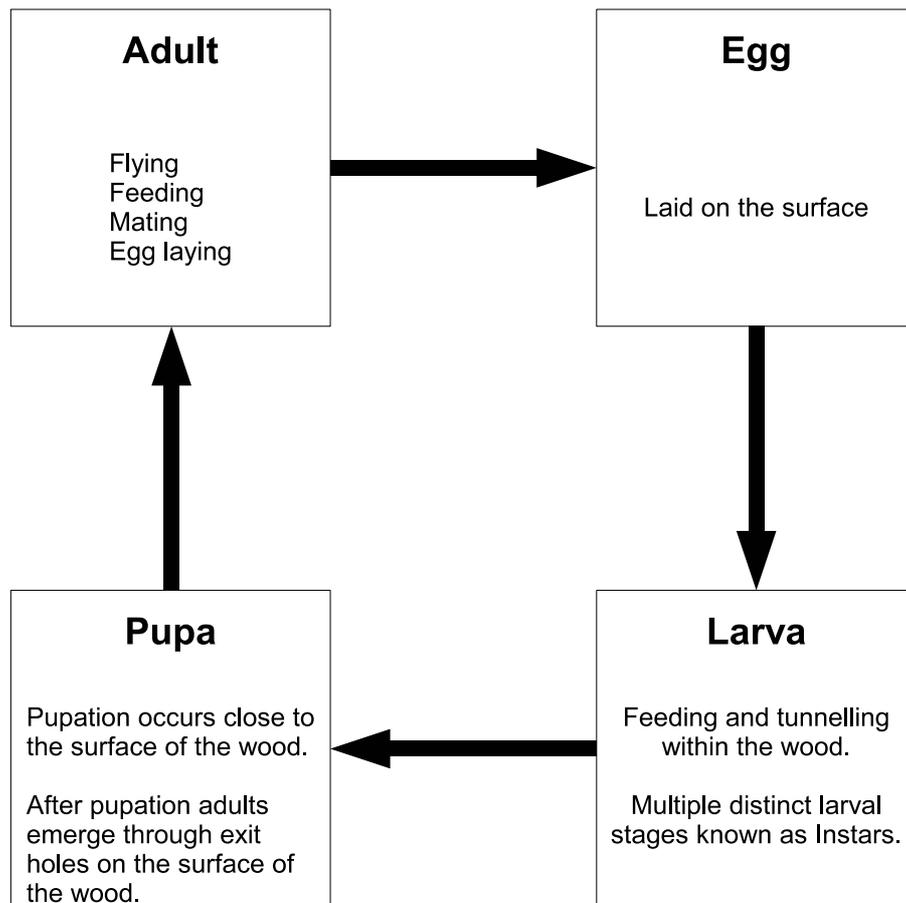
Figure 3.4: The Lifecycle of a Wood-Boring Beetle

The specifics of each of the stages within the insect's lifecycle varies between and sometimes within species depending on external influences such as temperature. For example, the length of time spent as an adult and the number of larval instars is known to vary (Adachi, 1994). The Cottonwood Borer (*Plectrodera scaltor*), a pest which attacts the roots of trees in the United States, is known to have at least five instars (Forschler and Nordin, 1991). Larvae of the Asian Longhorn Beetle may pass through up to 14 instars (Keena and Moore, 2010).

Like most insects, adult beetles produce detectable sounds using a number of the mechanisms detailed in section 3.3. *Hylotrupes bajulus*, a species native to the United Kingdom, is known to produce sound by stridulation for aggression, attraction and during mating (Breidbach, 1986). As was mentioned in section 3.3, the Death Watch Beetle produces

sound by striking for the purpose of attraction (Birch and Keenlyside, 1991). The author is not aware of any evidence to suggest that eggs or pupae produces detectable sounds, though as they are living it is assumed that very low level vibrations will be transmitted. There is very little literature concerning non-incidental sound production by beetle larvae. Stag Beetle (*Lucanus cervus*) larvae have been recorded producing non-incidental sounds using stridulation and these sounds have been used to distinguish it from other species (Harvey et al., 2011). It is possible that larvae of other beetle species produce as yet undiscovered non-incidental sounds. All wood-boring larvae produce incidental sounds as a by-product of their feeding and movement; these sounds will be discussed in detail in Section 3.5.

The requirements of this research mean that only sounds produced while the beetles are within the trees or wood need to be detected. Since adult beetles do not fall into this category any sounds which they may produce will not be considered; as there is no evidence to suggest that eggs or pupae produce detectable sounds the sounds of interest are therefore limited to the feeding and movement sounds produced by larvae.

3.5   Sounds produced by Larvae

This research concentrates on the detection of incidental sounds, primarily those produced as larvae feed. These sounds are therefore dependant on both the physical properties and behaviour of the lavae. To understand the nature of these sounds it is useful first understand various properties and characteristics of the larvae themselves.

When in larval form, one of a beetles primary activities is feeding. The larva feeds on the wood directly in front of it and moves forward into the newly opened cavity. Over a period of time a larva creates a tunnel through the wood by this process.

Larvae feed using highly sclerotised mandibles; Figure 3.5 is a diagram of a cerambycid beetle head showing the position of the mandibles. As a larva feeds it uses it's mandibles to grasp and break fibres of the wood; the breaking of these fibres sends vibrations through the wood potentially allowing the feeding activity to be detected at the wood's surface.
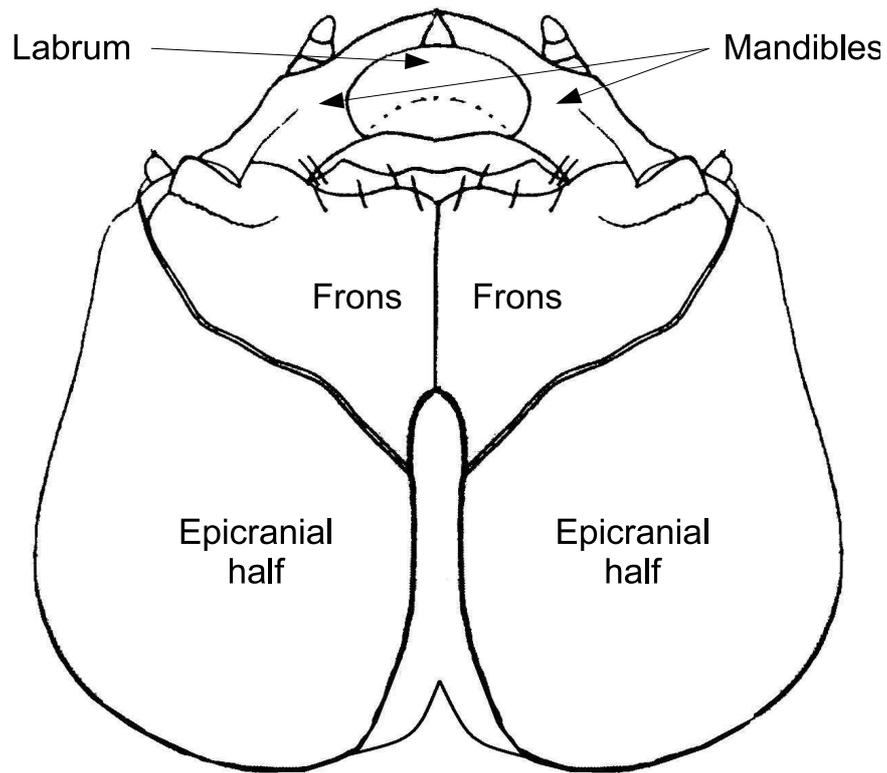
Figure 3.5: Diagram of cerambycid head (Adapted from (Duffy, 1968))

Figure 3.6 shows the waveform for a typical bite sound produced by an *Anoplophora glabripennis* larva, sampled at 44.1kHz with 16 bits per sample. This larva's bite has produced a single impulse like sound, possibly suggesting that only a single wood fibre has been snapped. Other bite examples, such as the *Agrilus planipennis* bite in Figure 3.7 contain multiple distinct elements. In this case the *A. planipennis* bite is more than 300% longer than the *A. glabripennis* bite.
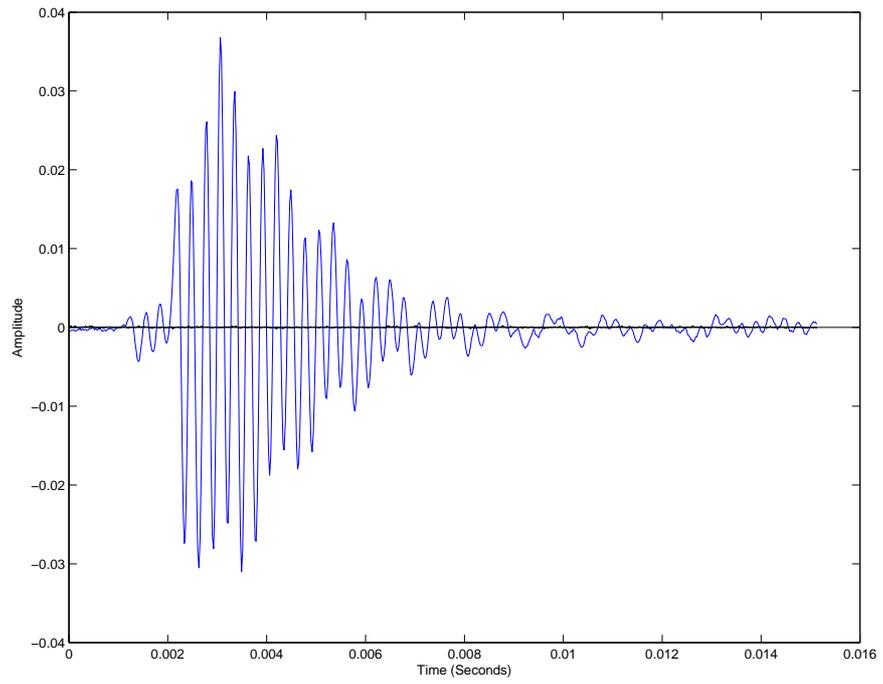
Figure 3.6: An *Anoplophora glabripennis* bite
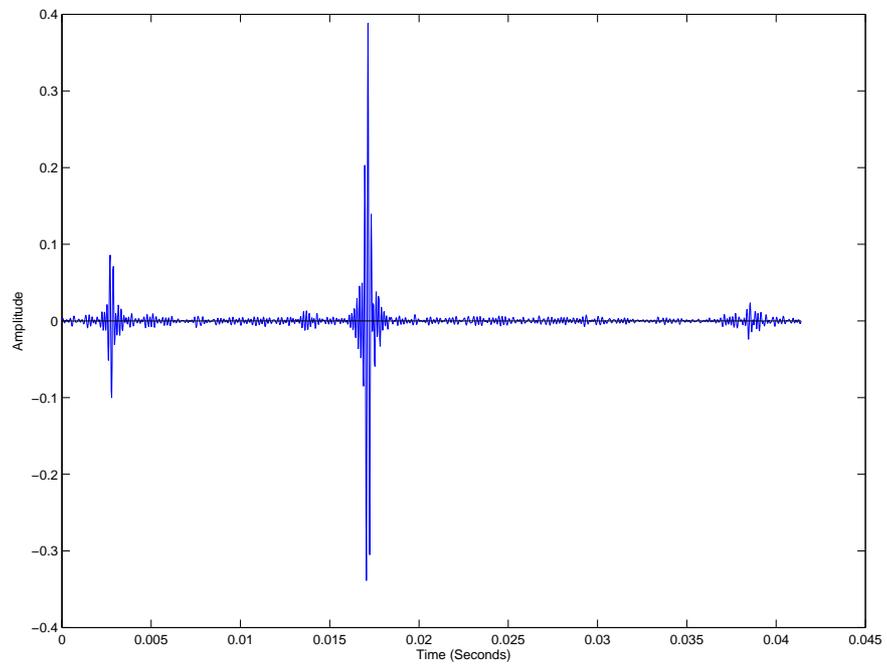
Figure 3.7: An *Agrilus planipennis* bite

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3.5.1 Variation within species

Relatively little is known about the variation in feeding behaviour of larvae or the sounds associated with it. It is however likely that the feeding behaviour will be influenced by a number of internal and external factors.

As a larva grows it progresses through a number of distinct stages. Insects in their larval form replace their exoskeletons (Esperk et al., 2007), and the Latin word 'Instar' is used to define the period between these replacements (Fischer, 1853). As a larva progresses into later instars it becomes physically larger. There are a number of ways in which this growth could affect feeding and the incidental sounds associated with it. A later instar larva will have larger mandibles and may be able to grasp a greater number of wood fibres and exert a greater force on them than an earlier instar larva. It is also possible that the feeding patterns will change as a larva develops, making it feed more or less frequently. In the case of *A. glabripennis*, larvae feed on different parts of the host wood as they develop through their Instars (Herard et al., 2009a).

Another consideration is the lifecycle of the insect. The life cycles of *A. chinensis*, *A. glabripennis* and *Agrilus planipennis* are discussed in sections 3.6.2, 3.7.2 and 3.8.2. The development and life-cycle of beetles is influenced by temperature. The effects of temperature variation on *Anoplophora glabripennis* were studied by Keena and Moore (Keena and Moore, 2010). They found that larvae would only develop at temperatures below $30\,°C$ and estimated that the minimum required temperature was $12\,°C$. A similar study on the effects of temperature variation on *A. malasiaca* was undertaken by Adachi (Adachi, 1994). Sets of larvae were kept at three temperatures: 20, 25 and $30\,°C$. No larvae kept at 25 or $30\,°C$ survived to the pupal stage.

Adachi also observed that "most larvae spent a several-month period without feeding before pupation". This suggests a potential problem for a system based upon acoustic detection, namely that larvae may spend significant periods of time producing no detectable acoustic emmissions. Larvae detection in these situations would require an active detection method such as X-ray or ultrasound reflection. Fleming *Et al* studied the detection of *A. glabripennis* larvae using non-contact 200kHz ultrasound imaging and concluded that the technique was not currently feasible (Fleming et al., 2005). The limitations of X-ray

technology for larvae detection have been discussed in Chapter 2.

Numerous other factors could potentially influence the feeding behaviour and development of larvae, such as wood moisture content or the species of the host. There are a great deal of unknowns regarding the behaviour of larvae, largely due to their inaccessibility when inside tree trunks.

3.5.2 Variation Between Species

In order for acoustic based species classification to be carried out the feeding sounds produced by larvae of different species must be sufficiently different from one another either in content or pattern of occurrence. In his 2007 thesis, Farr published classification success rates of over 96% between two beetle species, *Hylotrupes bajulus* and *Prionus coriarius* (Farr, 2007). These results suggest that there is a high degree of inter-species variation in the feeding sounds produced. Species classification will be considered in detail in Chapter 5.

3.6 Anoplophora chinensis (Citrus Long-Horned Beetle)

A. chinensis is a wood boring beetle in the family Cerambycidae. A similar species, *Anoplophora malasiaca*, is considered to be very closely related (EPPO, 2003), or in some cases as a form of the same species (Lingafelter and Hoebeke, 2002).

Figure 3.8: *Anoplophora chinensis* adult (Image provided by FERA, used with permission)

3.6.1 Geographical Distribution

Both *A. chinensis* and *A. malasiaca* are native to East-Asia. *A. chinensis* is found in China, Korea, Malaysia and Vietnam (EPPO, 2003). *A. malasiaca* is found in Japan and Korea (Hu et al., 2009). Within the past decade several infestations and outbreaks of *A. chinesis* have been found in Europe. These infestations are summarised in Table 3.2.

Location	Year	Reference
Italy	2000, 2008	(Maspero et al., 2007), (Gaag et al., 2010)
France	2003	(Herard et al., 2006)
Croatia	2007	(Vukadin and Hrasovec, 2008)
Netherlands	2007, 2009	(Gaag et al., 2010)

Table 3.2: *Anoplophora chinensis* outbreaks in Europe

There have been no reported outbreaks in the United Kingdom however interceptions have occured in 2005, 2008, 2009 and 2010 (FERA, 2011a).

3.6.2 Life Cycle

In it's native East-Asia, *A. chinensis* has a lifecycle of approximately one year (Lieu, 1945). *A. malasiaca* has a lifecycle of between 1-2 years (Adachi, 1994). In the infestation in Milan, Italy, a lifecycle of between 1 and 2 years has also been reported (Haack et al., 2010).

Adults emerge between April and August but are most abundant between May and July (FERA, 2008), (Maspero et al., 2007). Estimates vary from about 70 eggs laid per female (EPPO, 2003) to over 300 (Adachi, 1988). Maspero *et al.* found that incubation lasted between 15 and 20 days and is temperature dependant (Maspero et al., 2007). Exit holes are usually found near the base of tree trunks or on roots (FERA, 2010).

3.6.3 Morphology

Stage	Size	Reference
Adult	25 - 35mm	(EPPO, 2003)
Larva	50 - 60mm	(Maspero et al., 2007)
Pupa	27 - 38mm	(Lieu, 1945)
Egg	5 - 7mm x 1.7mm	(Lieu, 1945), (Haack et al., 2010)

Table 3.3: Basic Dimensions of *Anoplophora chinensis*

3.6.4 Hosts

A. chinensis has a large range of host plants (Gaag et al., 2010). These include *Acer* spp., *Alnus* spp., *Betula* spp., *Casuarina* spp., *Citrus* spp., *Litchi* spp., *Malus* spp., *Populus* spp., *Salix* spp. and *Ulmus* spp. (EPPO, 2003), (FERA, 2008).

3.7 Anoplophora glabripennis (Asian Long-Horned Beetle)

The Asian long-horn beetle is native to China. Adults are around 3cm long, have black with white spots and long black and white antennae. It's larvae are white and worm-like(USDA, 2007).

Figure 3.9: *A. glabripennis* adult (Image provided by FERA, used with permission)

3.7.1 Geographical Distribution

A. glabripennis is native to China and Korea (Hu et al., 2009). The first reported infestation outside Asia was in New York, USA, in 1996 (Haack et al., 1997). There have since been several infestations reported across the US and in Europe (Hu et al., 2009). Table 3.4 gives a summary of these infestations.

Location	Year	Reference
New York, US	1996	(Haack et al., 1997)
Chicago, US	1998	(Poland et al., 1998)
Braunau am Inn, Austria	2001	(Tomiczek et al., 2002)
New Jersey, US	2002	(Haack, 2003)
Toronto, Canada	2003	(Hu et al., 2009)
Gien, France	2003	(Herard et al., 2006)
Keukirchen am Inn, Germany	2004	(Benker et al., 2004)
Corbetta, Italy	2007	(Maspero et al., 2007)

Table 3.4: *A. glabripennis* outbreaks outside Asia

3.7.2 Life Cycle

Adults emerge between May and October (Li and Wu, 1993). Studies in China show that the beetles can travel over 1400 metres from their exit holes with a mean dispersal distance of 220-300 metres (Smith et al., 2000) to feed on leaves and young bark (EPPO, 2004). Eggs are laid in individual oviposition pits below the bark (Li and Wu, 1993). Around 32 eggs are laid per female per season (Wong and Mong, 1986). Adults emerge leaving round exit holes around 10mm in diameter. *A. glabripennis* uses both healthy and unhealthy trees as hosts.

3.7.3 Morphology

Stage	Size	Reference
Adult	25 - 35mm	(EPPO, 2004)
Larva	up to 50mm	(EPPO, 2004)
Egg	5 - 7mm	(EPPO, 2004)

Table 3.5: Basic Morphology of *A. glabripennis*

3.7.4 Hosts

A. glabripennis has been found on a number of species of host trees in the US and China. It primarily infests *Populus* spp., *Salix* spp., *Ulmus* spp. and *Acer* spp. (Haack et al., 2006).

Yang lists the major hosts of *A. glabripennis* in China as *Populus nigra*, *Populus deltoides*, *Populus dakhuanensis*, *Salix babylonica* and *Salix matsudana* (Yang et al., 1995).

3.8   Agrilus planipennis (Emerald Ash-Borer)

The Emerald Ash-Borer is a member of the family *Buprestidae*. The adults are metallic green coloured and infest Ash, usually causing death within 2 to 4 years of initial infestation. It is also known as *Agrilus marcopoli* and *Agrilus feretrius*. Adults leave distinctive D shaped exit holes in the trees they infest as they emerge(Forestry-Commission, 2004).

Figure 3.10: *Agrilus planipennis* adult

Photograph: Pennsylvania Department of Conservation and Natural Resources -

Forestry Archive, Bugwood.org

3.8.1   Geographical Distribution

The species is native to parts of Asia; specifically northeastern China (Yu, 1992), Korea (Ko, 1969) and Japan. It is also native to parts of far east Russia (Haack et al., 2002). There are numerous infestations across the USA since 2002 including Illinois, Indiana, and Ohio (APHIS, 2009). There have been no reported infestations in Europe. No interceptions have been reported in the United Kingdom but the species is considered to be a significant threat (Forestry-Commission, 2004).

3.8.2 Life Cycle

The entire life-cycle generally lasts 1 year although in some climates it can be 2 years (Cappaert et al., 2005). There are 4 larval instars and adults emerge in May or early June (Cappaert et al., 2005), (Wang et al., 2010). Approximately 10 days after emerging, females begin to lay eggs (Wang et al., 2010). Between 60 and 90 eggs are laid per female (Cappaert et al., 2005). Larvae feed under the bark in the cambium (See Figure 3.2) (EPPO, 2005). Adults emerge from exit holes high up in the tree's trunk or branches (EPPO, 2005).

3.8.3 Morphology

Stage	Length	Width	Reference
Adult	8.5 - 14.0mm	3.1 - 3.4mm	(EPPO, 2005)
Larva	26 - 32mm	1.5 - 5.1 mm	(EPPO, 2005),(Wang et al., 2010)
Pupa	11 - 16 mm	3-5 mm	(Wang et al., 2010)
Egg	1 - 1.4 mm	0.8 - 1.1 mm	(Wang et al., 2010)

Table 3.6: Basic Morphology of *Agrilus planipennis*

3.8.4 Hosts

As it's name suggests, the Emerald Ash Borer primarily feeds on Ash (*Fraxinus* spp.). Anulewicz *et al.* conducted a study to determine whether the beetle will feed on other tree species and found that no beetles developed to adults on non-Ash species (Anulewicz et al., 2008).

3.9 Summary

This chapter has discussed the source of the sounds which are to be detected. The transmission of sound through would and properties which may effect this have been considered.

The categories of sounds produced by insects have been outlined along with the mechanisms which are used to produce them. The sounds produced by wood-boring beetle species specifically have been considered and the feeding sounds produced by larvae inside

wood have been identified as the only suitable acoustical indicator of an infestation.

The chapter has concluded with case studies on three species of beetle, all of which are considered to be INNS.

Chapter 4

Acoustic Monitoring and Automated Detection

Automated acoustic detection can be considered as a two stage process; the first is the monitoring or capturing of audio data by means of an acoustic sensor such as a microphone or bi-morph. The second stage is the real-time analysis of the incoming audio data to provide acoustic event extraction. This generalised model is represented in Figure 4.1.

This chapter begins by briefly describing the two categories of recording methods, substrate and airborne, before examining the different methods which have been used to monitor the acoustic emissions of wood boring pests. Section 4.1.2 covers the selection of acoustic sensors and includes the results of testing which was used to compare their performance.

Section 4.2 covers the task of automated detection and a number of methods by which it can be performed. A novel technique known as Fractal Dimension Detection is introduced in section 4.2.3 and its performance relative to other methods is investigated. The chapter concludes with detection results.

4.1 Acoustic Monitoring

Bio-acoustics is a wide field ranging from the general, such as biodiversity assessment (Sueur et al., 2008), (Riede, 1993), to the specific, such as the automated identification of bird species (Chesmore, 2001) and crickets (Potamitis et al., 2007). Acoustics have been
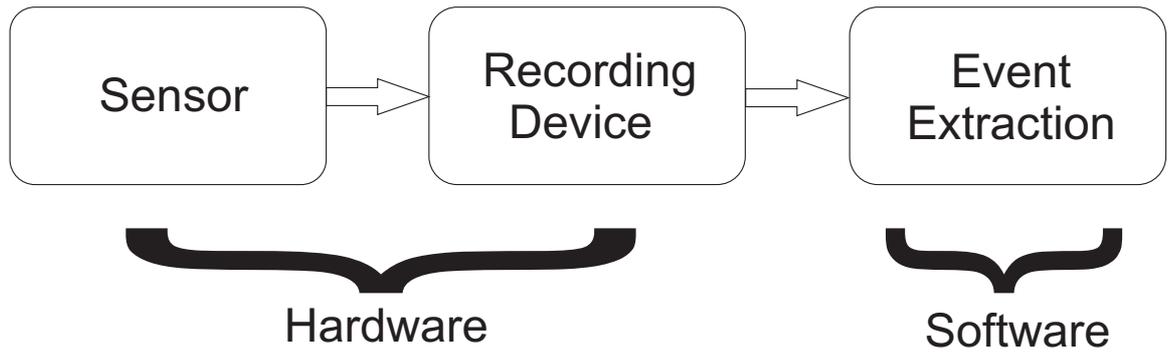
Figure 4.1: Acoustic Monitoring and Detection Process

used as a method for monitoring various animals for several decades. The approaches taken can be broadly separated into two groups, substrate and airborne. A substrate recording is one in which the sensor is in contact (directly or indirectly) with the subject being recorded. This method is most frequently used for monitoring insects but has also been used for larger animals; examples include the bio-seismic monitoring of large mammals (O'Connell-Rodwell et al., 2001) and acoustic monitoring of cattle (Clapham et al., 2011). Airborne recording methods tend to be used when the subjects are likely to move over a large area. The sensors used are often specialised to suit the type of sound produced, such as the use of ultrasonic sensors to monitor bats (Vaughan et al., 1997) and hydrophones to monitor sperm whales (Mellinger et al., 2002). This project will concentrate on substrate recording methods since the subjects to be recorded are contained within another substrate; the wood or timber, and have restricted movement.

4.1.1 Acoustic Monitoring of Insects in plants and timber

A number of acoustic monitoring methods have been used in the past to record the activity of insect larvae in plants and timber. Brain suggested in 1924 that it may be possible to detect insects in grain and fruit using acoustics (Brain, 1924).

Colebrook successfully recorded *Xestobium rufovillosum* larvae in timber using a piezo-electric microphone (Colebrook, 1937). The sensors were placed on the surface of the timber samples in a non-invasive manner.

Mankin *et al.* used an accelerometer to detect *Cephus cinctus* and *Metamasius callizona* in Wheat and Bromeliads respectively (Mankin et al., 2004). One of the difficulties

encountered with this method was attaining a suitably good interface between the accelerometer and the sample plant. This can be attributed to the soft plant materials to which the sensors were attached.

Fleming *et al.* used a non-contact ultrasonic sensor to detect *Plectrodera scalator* larvae in wooden blocks. The technique was successful in detecting the drilled cavities in the blocks but not the larvae placed inside them (Fleming et al., 2005).

A method sucessfully used by Mankin *et al.* to detect *Anoplophora glabripennis* in trees used a combination of piezoelectric sensors attached to screws which were inserted into the wood (Mankin et al., 2008). A disadvantage of this method is that it is invasive and may not be feasible for use on high value trees.

Rohitha *et al.* used electret microphones to detect *Oemona hirta* larvae in wood (Rohitha et al., 1994). This approach required the sample to be placed in an acoustically isolated chamber in order to detect sounds produced by the larvae above background noise. The isolation requirements and the use of a gain of 50000 mean that this method could only be used in laboratory conditions.

Piezoeletric sensors were also used by Potamitis *et al.* to detect *Rhynchophorus ferrungineus* (Red Palm Weevil) (Potamitis et al., 2008). In this case the sensor probes were inserted into the tree rather than being mounted on the surface.

Farr investigated a number of acoustic sensors for use in detecting beetle larvae (Farr, 2007) in hard and soft plant material. Sensors considered were bi-morphs, piezoelectric transducers and microphones. He found that the bi-morph sensors were very fragile and prone to breaking when being attached or removed from samples. Piezoelectric sensors were concluded to be the most sensitive of the three investigated. Table 4.1 summarises the sensors which have been used to record various insects in plants and timber. The term invasive is used here to distinguish between those approaches which penetrate the surface of the wood or plant material, and those that do not.

Sensor Type	Invasive	Details	Reference
Piezo-electric micro-phone	No	Detection of *Xestobium rufovillosum*	(Colebrook, 1937)
Ultrasonic sensors	No	Monitoring of termites in wood	(Fujii et al., 1990)
Electret microphone	No	Recording of *Oemona hirta* in wood	(Rohitha et al., 1994)
Accelerometer	No	Detection of *Cephus cinctus* and *Metamasius callizona* in Wheat and Bromeliads	(Mankin et al., 2004)
Piezo sensors, bi-morphs, microphones	No	Detection of various wood boring-beetle species	(Farr, 2007)
Piezo sensors	Yes	Detection of *Anoplophora glabripennis*	(Mankin et al., 2008)
Piezo sensors	Yes	Detection of *Rhynchophorus ferrungineus*	(Potamitis et al., 2008)

Table 4.1: Summary of sensors used to detect insects in plants and timber

4.1.2 Sensor Selection and Coupling

The requirements for the sensors are that they are to be low cost, simple to attach and provide a good acoustic coupling with the wood or tree. The attachment of the sensors must be non-invasive, that is to say that they must not penetrate the surface or in any way damage the sample. This restricts the range of attachment methods which can be used. The use of waveguides inserted into the sample in order to improve acoustic coupling such as those used by Mankin *et al.* is therefore not a viable option (Mankin et al., 2000).

An investigation into the efficiency of multiple types of sensors has been carried out. Since the completion of the previous DEFRA project (PH0191) (Farr, 2007), multi-axis accelerometers have decreased significantly in cost, to around £10 per unit. These sensors could potentially be more sensitive than piezo-electric devices so a number of tests

were carried out using them. Three sensor types were investigated using two experiments. Figure 4.2 shows the equipment set-ups used. An Oak log had a hole drilled into one end into which a speaker or solenoid was inserted. The sensor being tested was then attached to the surface of the log, positioned directly above the cavity or at a defined distance from it along the surface. The piezo sensors were attached to the log using elastic bands. Attempts to attach the accelerometer circuit using this method resulted in no signal being detected. The results below were obtained by holding the accelerometer circuit firmly against the bark.

(a) Embedded piezo-speaker (b) Embedded solenoid
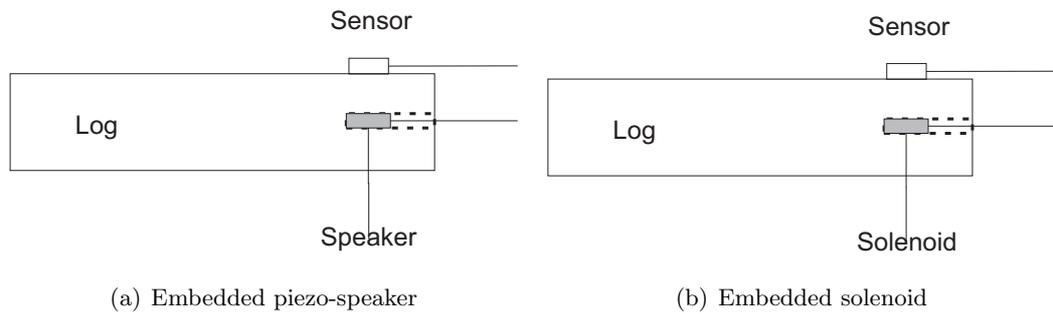
Figure 4.2: Sensor coupling experiment set-up

Table 4.2 lists the types of sensors tested. The first two sensors are simple piezo-electric devices which are passive. The final sensor is a 2-axis accelerometer although only a single axis was used. The accelerometer is a powered sensor which required mounting on a printed circuit board.

Sensor Type	Name Used	Details	Unit Cost (Approx)
Murata PKLCS1212E2000-R1	Piezo Sensor 1	Square piezo with 2kHz resonant frequency	£2
Kingstate KPEG116	Piezo Sensor 2	Circular piezo with 2kHz resonant frequency	£1
Analog Devices ADXL322JCP	Accelerometer	2-Axis Accelerometer	£10

Table 4.2: Table of sensors tested

The first experiment used a piezo-speaker inserted into the log. Sine waves with amplitude 12V p-p, at various frequencies were played through the speaker and the voltage

at the sensor recorded to assess the relative performance. The results are shown in Figure 4.3.
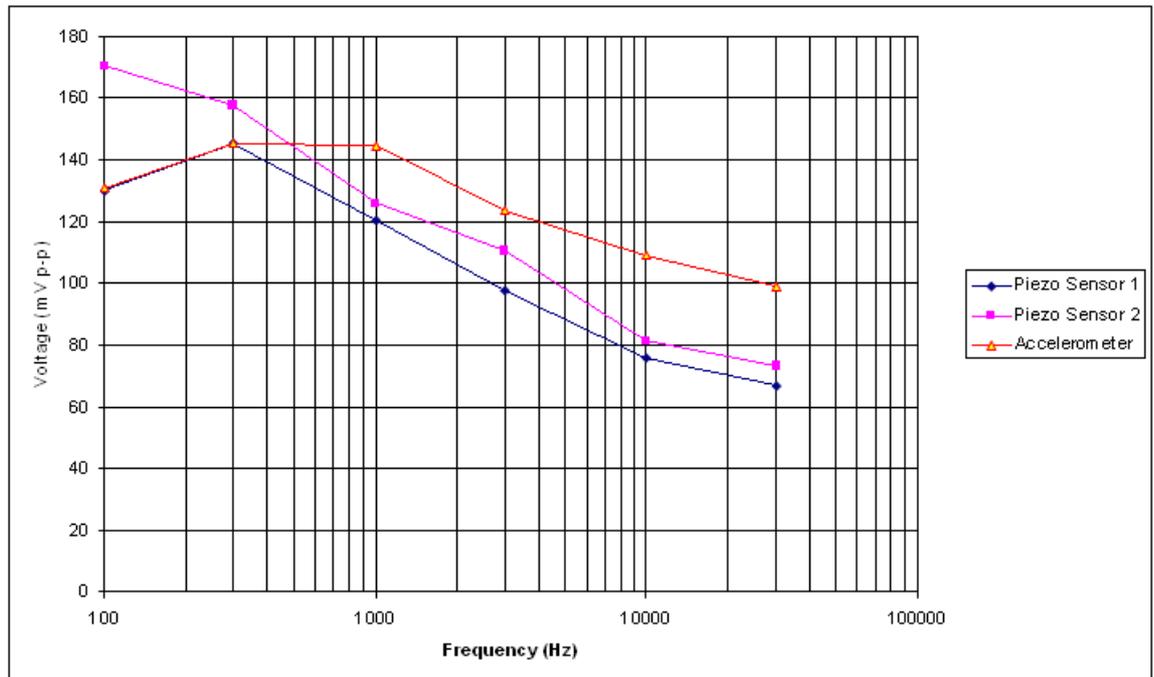
Figure 4.3: Voltage at sensor vs input frequency

The second experiment used a solenoid inserted into the log to provide a sound impulse with a consistent amplitude. The sensors were placed at various distances from the solenoid along the surface of the log. The results can be seen in Figure 4.4.

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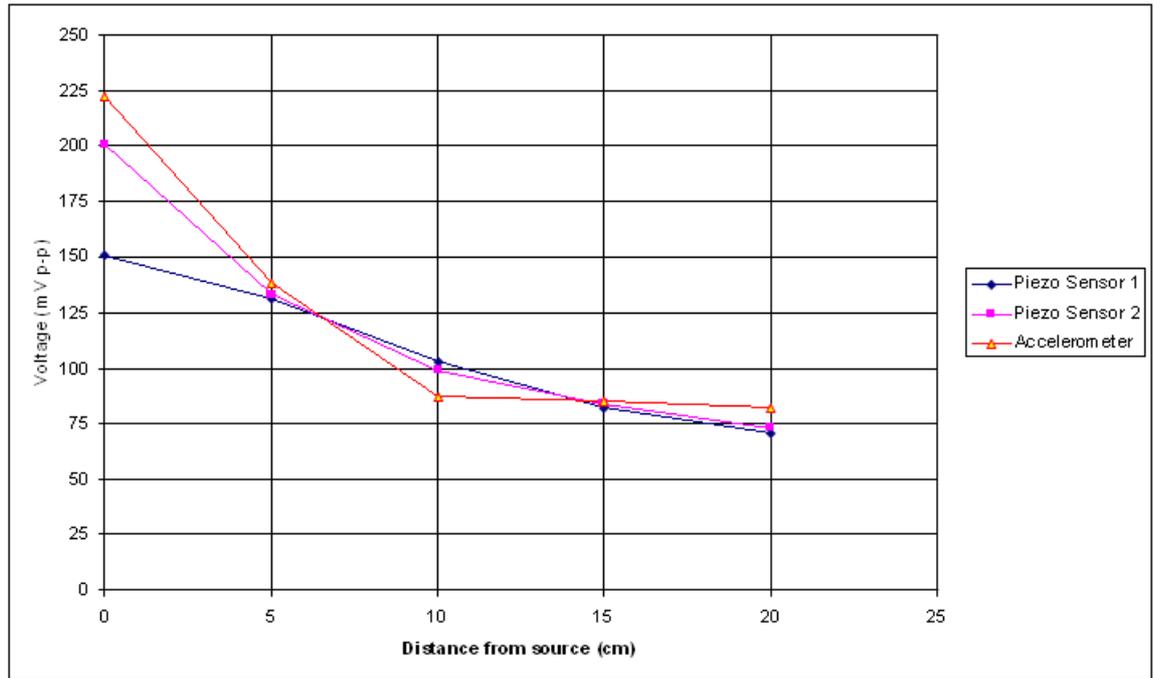
Figure 4.4: Voltage at sensor vs distance from source

It can be seen from the results that the accelerometer sensor provided no significant improvement in sensitivity over the piezo sensors. The accelerometer sensor is more expensive, requires external power and is more complex. In the experiment using a speaker emitting sine-waves the accelerometer showed greater sensitivity however it was far more difficult to achieve a good acoustic coupling and as described above, the sensor had to be held in place. For these reasons a decision was taken to concentrate on the use of piezo-electric sensors.

4.2 Automated Detection

Automated detection is the ability to have a system extract certain acoustic events from background noise without needing human interaction. The acoustic events in this case will be those generated as larvae feed. Various signal processing approaches have been used to automatically detect wood-boring insects. Some methods treat event extraction and classification as two distinct tasks, others combine the two stages into a single process. Here the extraction of acoustic events is being considered separately to species identification for a number of reasons. Firstly, the range of sounds produced within trees or wood is very limited. It is very unlikely that sounds which have a similar length to those produced by

larvae will be produced within a tree or cut wood. The primary aim of the system is to detect larvae rather than to identify their species. It is important that the system can detect bites with amplitudes as low as possible which may not contain sufficient information above the noise level to enable successful species identification. The proportion of audio information which is related to larval feeding as opposed to noise is very low; since the system is to be implemented in real-time, this seperation of tasks will be needed to limit the amount of data which is passed on to the species identifier.

A computationally simple system was used by Webb *et al.* to detect larvae recorded in fruit and grain (Webb et al., 1988). Samples were placed in a sound insulated chamber and the recordings made passed through a band-pass filter. A simple amplitude threshold was then sufficient to detect larval activity within the recording.

Mankin *et al.* used a combination of amplitude thresholds, spectral profiling and temporal pattern analysis for the automated detection and identification of *Anoplophora glabripennis* (Mankin et al., 2008). Recorded audio was first band-pass filtered between 200Hz and 5kHz. An amplitude threshold was defined as a multiple of a moving average of the amplitude using 0.186s intervals. When this threshold was exceeded a power spectrum was generated using a 512 sample Fast Fourier Transform centred about the largest peak within the next 6ms of audio. This power spectrum data was then either used to create a spectral profile or to classify against a spectral profile already in existence. Spectral profiles were generated by comparing the current power spectrum against that in the profile. If the mean of the squared differences between spectrum levels was below a predefined threshold the current power spectrum would be in the profile. Classification used a similar predefined threshold to determine whether the power spectrum of a detected impulse was closed enough to the profile.

4.2.1 Energy Detection

Ultra short time energy detection (USTED) was used by Potamitis to extract acoustic events from recordings of crickets (Potamitis et al., 2006). Recognition rates of non-incidental stridulation sounds of around 95% were obtained using this method. Farr adapted USTED for the extraction of incidental sounds produced by larvae bites (Farr,

2007). This required the frame size to be increased in order to successfully detect the lower amplitude larval bites.

The method itself relies on the assumption that an acoustic event has an energy content which is sufficiently higher than the average for the recording. The energy of successive segments of audio is measured and a threshold is applied to determine whether a segment contains or forms part of an acoustic event. Audio data is separated into M frames of a fixed length:

$$M = N/L \tag{4.1}$$

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:

$$E_{use}(k) = \sum_{i=1}^{L} [x(kL+i)]^2, k = 0, ..., M-1 \tag{4.2}$$

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 audio data (Potamitis et al., 2006).

The group sized used should be selected based upon the length of event which is being detected. Potamitis used a group size of 5 samples, $113\mu s$ at 44.1kHz (Potamitis et al., 2006). In order to use this method to detect low level incidental sounds produced by beetle larvae, Farr increased the group size to 44 samples, around 1ms at 44.1kHz (Farr, 2007). Figure 4.2.1 shows an example bite with energy values calculated using this method overlayed.
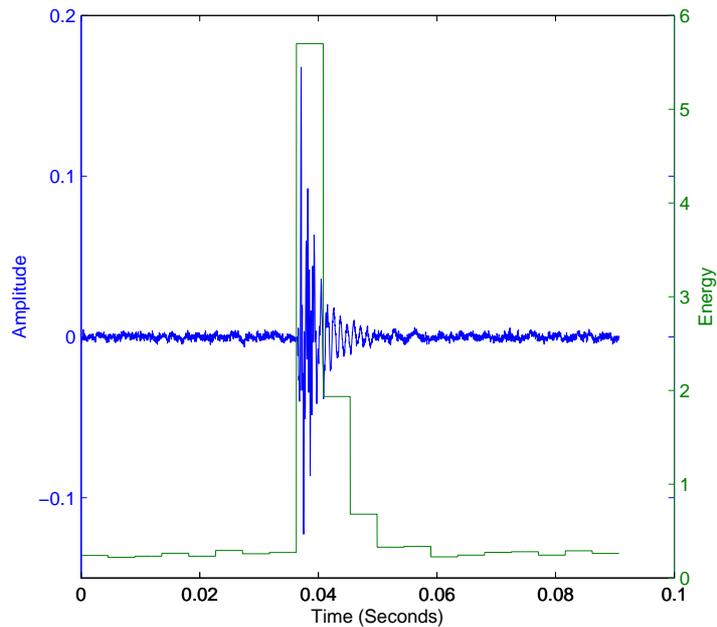
Figure 4.5: Bite with energy overlayed

4.2.2 Fractal Dimension

Fractal dimension has been used as a tool for analysis of various acoustic signals. Most commonly it is used to analyse waveforms over a relatively long period of time such as those produced by monitoring organ activity and function. Yambe *et al.* used fractal dimension to detect variations in cardiac function. This approach was used due to the non-linearity of heart rate variability (Yambe et al., 1999). Similar techniques were later used to analyse changes of fetal heart rate during pregnancy and by (Hotta et al., 2005) to analyse heart rate variability and mortality in the elderly. A fractal dimension based approach using Higuchi's algorithm has also been used to compare the electrocortical activity of rat brains before and after injury (Spasic et al., 2005).

Each of these applications uses fractal dimension to analyse changes of complexity in non-linear waveforms. Fractal dimension has the potential to be used for acoustic event detection if the event in question has a suitably differing complexity to the surrounding noise. Extracting acoustic events using fractal dimension detection relies on the concept that shapes can have a non-integer, or fractal, dimension. The fundamental concepts behind fractal dimension will be explained in here and their application to event detection

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in the next section.

By the late 19th century, mathematicians had determined that the definition of dimension as an integer number of coordinates was unsatisfactory (Cantor, 1890). To understand non-integer dimension it is necessary to determine a mathematical basis from which our concept of the traditional '1, 2 and 3' dimensions is derived. This is most simply approached by considering self-similarity. A line, for example, is one dimensional and can be doubled in length to produce two self similar shapes. A square can be doubled in length and width to produce four self similar shapes. Similarly a cube can be doubled in height, length and width to produce eight self similar shapes (Lanius, 2007). Table 4.2.2 shows these shapes, their dimensions and the number of self similar copies generated when scaled by a factor of two.

Shape	Dimension	Self Similar Copies	Scaling Factor
Line	1	2	2
Square	2	4	2
Cube	3	8	2

Table 4.3: The dimensions of common geometric shapes

This non-integer understanding of dimension was formalised by Hausdorff in 1919 and is known as the Hausdorff Dimension (Hausdorff, 1919). The dimension can be defined as:

$$D = \frac{log(N)}{log(r)} \tag{4.3}$$

where N is the number of self similar shapes and r is the scaling factor (Devaney, 1995).

This concept was later developed and the term fractal dimension coined to describe the non-integer dimension of geometric shapes (Mandelbrot, 1983). It can be applied to complex geometric shapes to calculate a non-integer dimension. The Sierpinski triangle (Figure 4.6), for example, appears to the eye to have a dimension of somewhere between one and two.

Scaling Factor   Self similar shapes

1   1

2   3

4   9
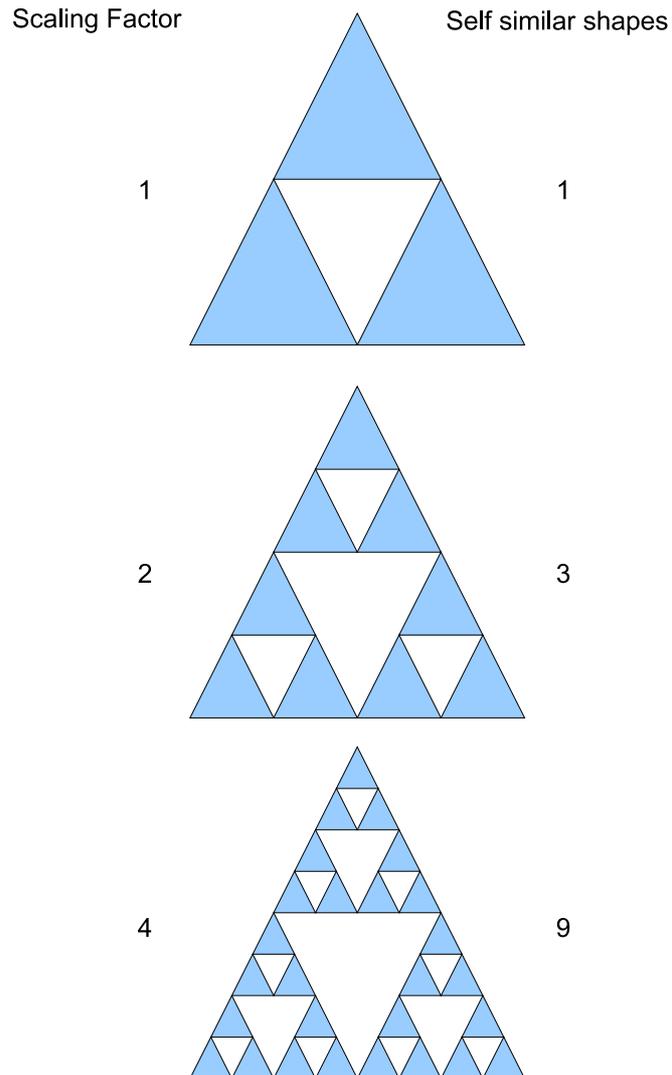
Figure 4.6: Sierpinski Triangle

Equation 4.3 can be applied to Sierpinski's Triangle using either of the scaling factors and self similar shape numbers given. The dimension can then be calculated as:

$$\frac{log(9)}{log(4)} = \frac{log(3)}{log(2)} = 1.59 \tag{4.4}$$

Fractal dimension can also be easily calculated for self-similar curves. The Koch curve (Figure 4.7) (Koch, 1904) is a self similar curve which can be generated from a straight line by the iterative process described below:

1. Divide the line into three equal lengthed segments.

2. Form an equilateral triangle pointing upwards using the middle segment as a base.

3. Remove the original middle segment.
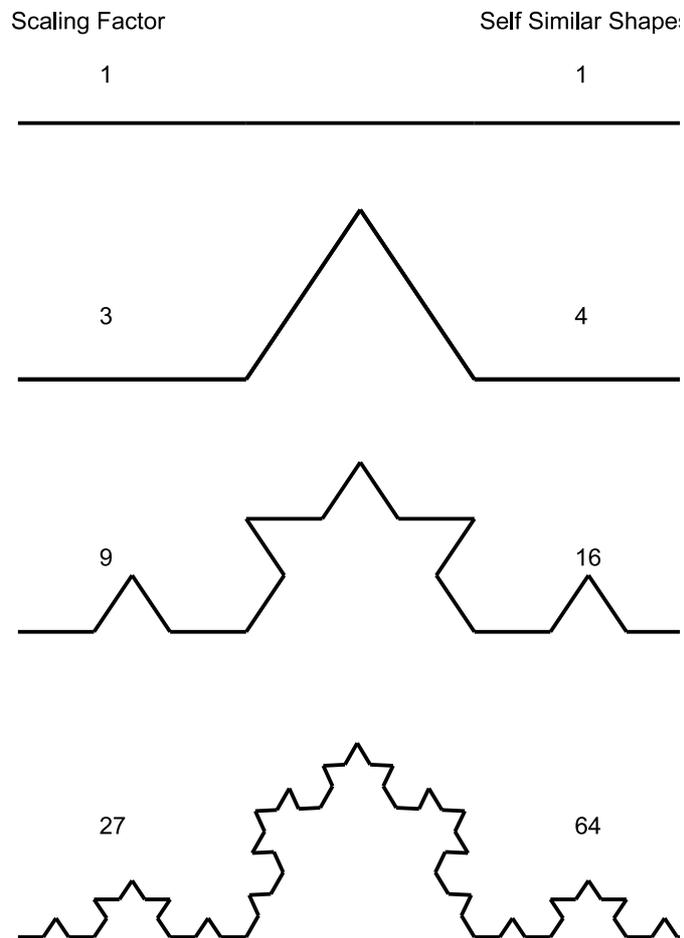
Figure 4.7: Koch Curve

The fractal dimension for the Koch curve can be calculated using equation 4.3 as:

$$\frac{log(4)}{log(3)} = 1.26 \tag{4.5}$$

The fractal dimension value of a shape can be considered to provide an estimate of it's complexity (Hitchcock, 2003).

4.2.2.1   Methods for estimating the fractal dimension of time-series

Fractal dimension is difficult to calculate directly and several different methods of estimation are used (Schepers et al., 1992), (Esteller et al., 2001). One of the most widely used fractal dimension estimation methods was published by Higuchi in his 1988 paper (Higuchi, 1988). For a time series with N values, $X(1), X(2), ..., X(N)$, k new time series are constructed where $m = 1, ..., k$:

$$X_k^m = X(m), X(m+k), X(m+2k), ..., X(m + \left[\frac{N-m}{k}\right] \cdot k) \tag{4.6}$$

The length of the curves, $L_m(k)$, are then calculated using equation 4.7.

$$L_m(k) = \frac{1}{k} \left\{ \left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} |X(m+ik) - X(m + (i-1) \cdot k)| \right) \frac{N-1}{\left[\frac{N-m}{k}\right] \cdot k} \right\} \tag{4.7}$$

$L(k)$, the length of the curve for the time interval k, is calculated as the average of all $L_m(k)$ curves:

$$L(k) = \frac{1}{k} \cdot \sum_{m=1}^{k} L(m, k) \tag{4.8}$$

D, the estimated fractal dimension, is the slope of a log/log plot of $L(k)$ against $1/k$ calculated by least-squares fit.

Another commonly used method was proposed by Katz (Katz, 1988). For a curve containing N values, $x_0 \ldots x_N$, the length, L, is calculated as the sum of the distances between adjacent points.

$$L = \sum_{i=1}^{N-1} dist(i, i+1) \tag{4.9}$$

D, the estimated fractal dimension, is calculated using equation 4.10 where d is the maximum distance between any two points on the curve.

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$$D = \frac{log(N-1)}{log(N-1) + log(\frac{d}{L})} \tag{4.10}$$

In his 1998 paper Sevcik proved that Katz' method was flawed in that as N, the number of samples, is increased, the estimated fractal dimension tends to 1 (Sevcik, 1998). Sevcik produced an alternate method to overcome this. For a given waveform containing N values, x_0, ..., x_N, an approximation to the fractal dimension is calculated using the following method. The waveform is first normalised in both axes and mapped to a unit square using equations 4.11 and 4.12.

$$x_i^* = \frac{x_i}{x_{max}} \tag{4.11}$$

$$y_i^* = \frac{y_i - y_{min}}{y_{max} - y_{min}} \tag{4.12}$$

L, the length of the curve in the unit square is calculated by summing the distances between adjacent normalised points (Equation 4.13).

$$L = \sum_{i=1}^{N-1} dist(i^*, (i+1)^*) \tag{4.13}$$

D, the approximate fractal dimension of a waveform, is calculated using equation 4.14.

$$D = 1 + \frac{ln(L)}{ln(2 * (N-1))} \tag{4.14}$$

In order for an estimation method to be useful for event detection it does not necessarily need to produce a highly accurate estimate of fractal dimension. Since the end system needs to perform the event detection task in real-time, an algorithm was selected based upon computational simplicity rather than mathematical accuracy. Using big-O notation, Higuchi's algorithm has a complexity of $O(N^2)$ whereas Sevcik's has a complexity of $O(N)$.

In practice 'real-time' means that detection results are provided to the user at one second intervals since the average fractal values, as used in equation 4.15 are calculated

using one second long chunks of audio. The system as a whole must therefore be able to analyse each chunk of audio before another is presented. On modern PC hardware the time taken for fractal dimension analysis calculation is insignificant since it is in the order of milliseconds. It is however, envisaged that the detection methods may be implemented on embedded hardware with significantly lower processing power in the future. For these reasons, Sevcik's method was chosen for use in the detection system.

4.2.3 Fractal Dimension Detection

Acoustic events can be detected using fractal dimension by segmenting the waveform in a similar way to USTED. Audio is segmented into frames of equal length and the fractal dimension of each frame calculated using equations 4.11 to 4.14. A threshold is then applied to these values to determine whether a frame contains an acoustic event. Figure 4.2.3 shows an example bite with fractal dimension values overlayed.
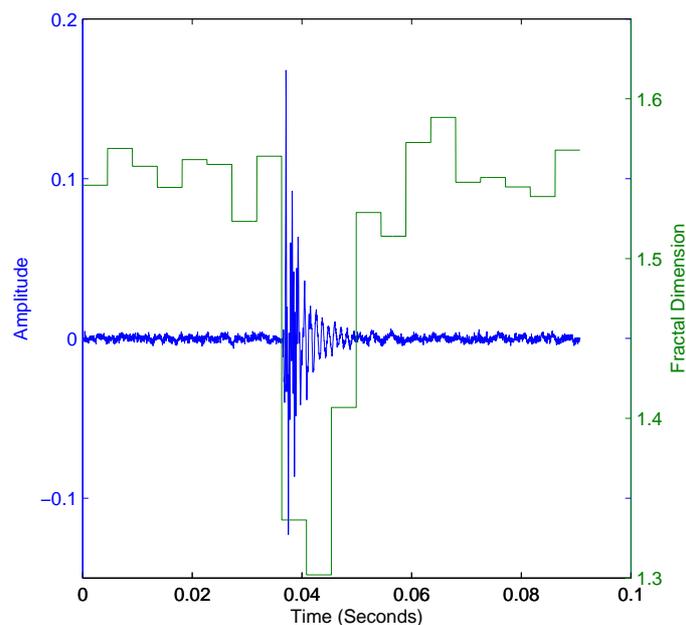
Figure 4.8: *Anoplophora glabripennis* bite with Fractal Dimension overlayed (Frame size 200 samples)

4.2.4 Comparison of detection methods

In order to compare the two bite detection methods a number of sample audio files were generated to test the relative performance of each method.

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One hundred individual bite sounds were extracted from recordings and each was placed at a known position into one second long audio clips consisting entirely of white noise. Each bite was merged with noise at multiple different signal to noise ratios to generate a set of five hundred sample audio files with which to test the detection methods.

A second test using automatically generated 1kHz sine waves of length 10 milliseconds, in place of real bite sounds was also performed to the same test specifications. The frequency and length of the sine wave were chosen to give it similar properties to a real larval bite albeit without any decay over time. It also enabled a direct comparision between the performance of the two methods using a strictly defined repeatable input.

Fractal dimension and energy values were calculated for each frame within the test waveform. The fractal dimension and energy values for the first frame containing the 'event' were measured as distance from the mean value in multiples of the standard deviation according to equations 4.15 and 4.16.

$$F_{dist} = \frac{|D_{event} - \overline{D}|}{\sigma} \tag{4.15}$$

$$E_{dist} = \frac{|E_{event} - \overline{E}|}{\sigma} \tag{4.16}$$

Figures 4.9 and 4.10 show E_{dist} and F_{dist} plotted against signal to noise ratio for embedded bites and embedded sine wave respectively.
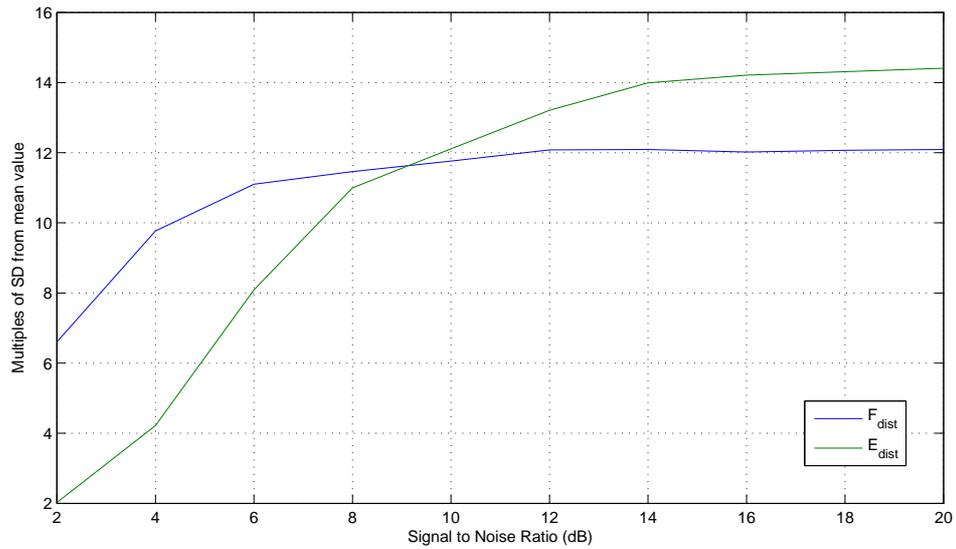
Figure 4.9: Fractal Distance and Energy Distance vs Signal to Noise Ratio (Embedded Bites, Frame Size 200 Samples)
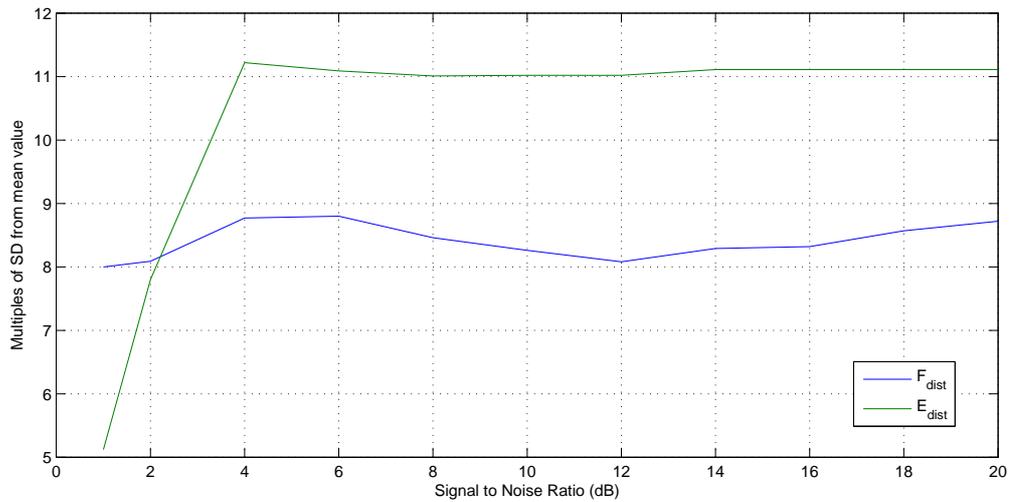
Figure 4.10: Fractal Distance and Energy Distance vs Signal to Noise Ratio (Embedded Sine Wave, Frame Size 200 Samples)

Ultra short time energy outperforms fractal dimension in terms of distance from mean value when detecting high signal to noise ratio events. This does not however suggest that energy detection provides any advantage in terms of detection since both F_{dist} and E_{dist} at high signal to noise ratio are clearly sufficient for detection. At lower signal to noise ratios fractal dimension outperforms energy detection for both embedded bites and

embedded the sine wave. This is significant since at these low signal to noise ratios F_{dist} and E_{dist} are closer to the threshold level so the advantage that fractal dimension has in terms of distance from mean value will enable bite detection at lower signal to noise ratios.

At a signal to noise ratio of 4, the embedded bites produces fractal values which are on average 9.77 standard deviations away from the mean whereas the equivalent mean energy detection value is only 4.22. At a signal to noise ration of 2, the figures are 6.61 for fractal dimension and 2.03 for energy detection; representing a 3.26 factor advantage.

4.2.5 Frame sizing

The frame size used to segment the waveforms will have an impact on the ability to distinguish between bites and background noise. To measure this effect the audio files with 10dB signal to noise ratio events from the previous test were analysed using varied frame sizes. Figures 4.11 and 4.12 show the results of this analysis. In both cases the x-axis is the frame size multiple which is calculated using the average event length over all test audio files.
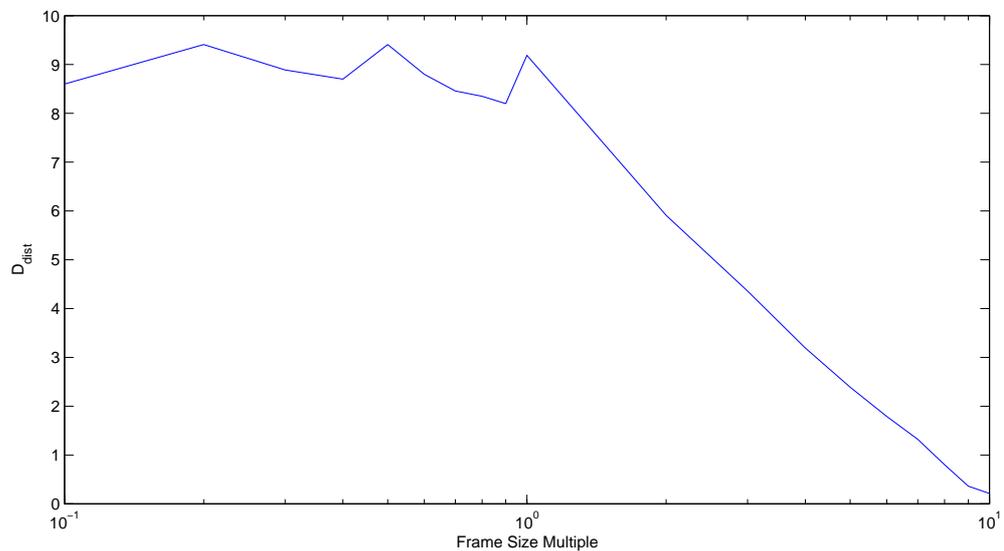
Figure 4.11: Fractal Distance vs Frame Size Multiple for embedded sine wave at 10dB
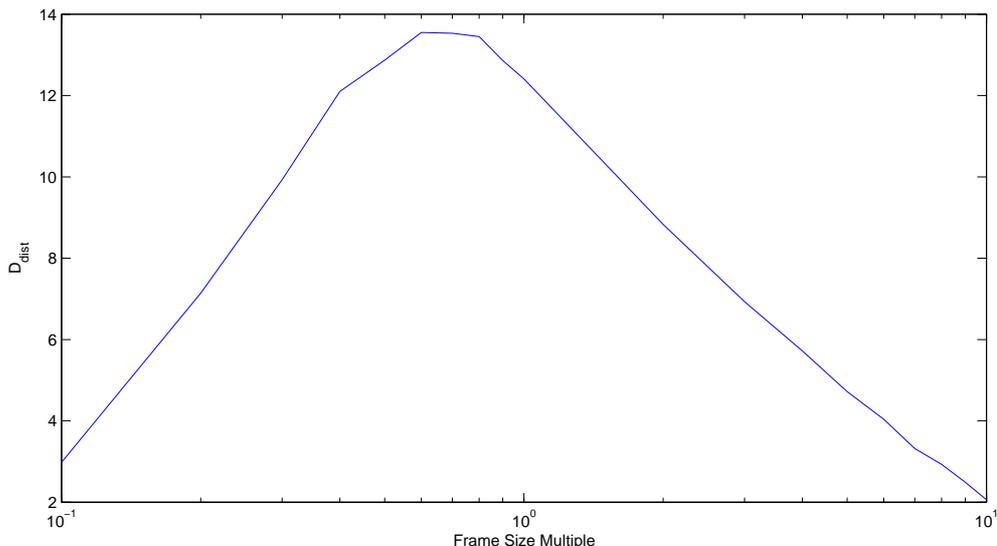
Figure 4.12: Fractal Distance vs Frame Size Multiple for embedded bites at 10dB

In both cases D_{dist} decreases significantly when the frame size multiple is greater than one. In these situations each frame contains a proportion of audio containing purely noise which causes D_{event} to be closer to $\bar{D}$. The value of D_{dist} for the embedded sine wave remains relatively stable for frame size multiples less than one. Given the cyclic nature of the wave this is unsurprising since the fractal dimension should be constant throughout it's length. If the frame size were to be decreased further it could be expected that D_{dist} will decrease as the low number of samples negatively affect the accuracy of fractal dimension estimation.

The peak D_{dist} value for the embedded bites is found when the frame size multiple is 0.6 and then decreases with frame size. The fractal dimension of a bite varies throughout it's length and the most useful portion in terms of event detection appears to be in the centre. This result demonstrates that the most effective way of detecting bite events may be to use a smaller frame size than the average bite length and to expand the event by a fixed number of samples either side.

4.2.6 Vertical Threshold

The level at which the D_{dist} threshold is set is crucial in achieving optimum bite detection performance. If set too high, bites will be left undetected, if set too low segments of noise

may be falsely detected as bites.

Bite detection is performed by segmenting the incoming audio into blocks one second in length. Each block is then further segmented into frames and the FD calculated for each frame. The distance from mean for each frame is then calculated using Equation 4.17 where D is the fractal dimension for the current frame and $\overline{D}$ is the mean over all frames within the block.

$$D_{dist} = \frac{|D - \overline{F}|}{\sigma} \tag{4.17}$$

In order to determine the optimum D_{dist} threshold level the performance of the detection system over a range of threshold levels has been tested. The rate of false positive detection was measured using artificially generated white noise and ambient sound recorded in a vacant laboratory. The rate of true positive detection of bites was measured using a recording of *A. glabripennis*. The relationship between detection rates and vertical threshold is shown in Figure 4.13.
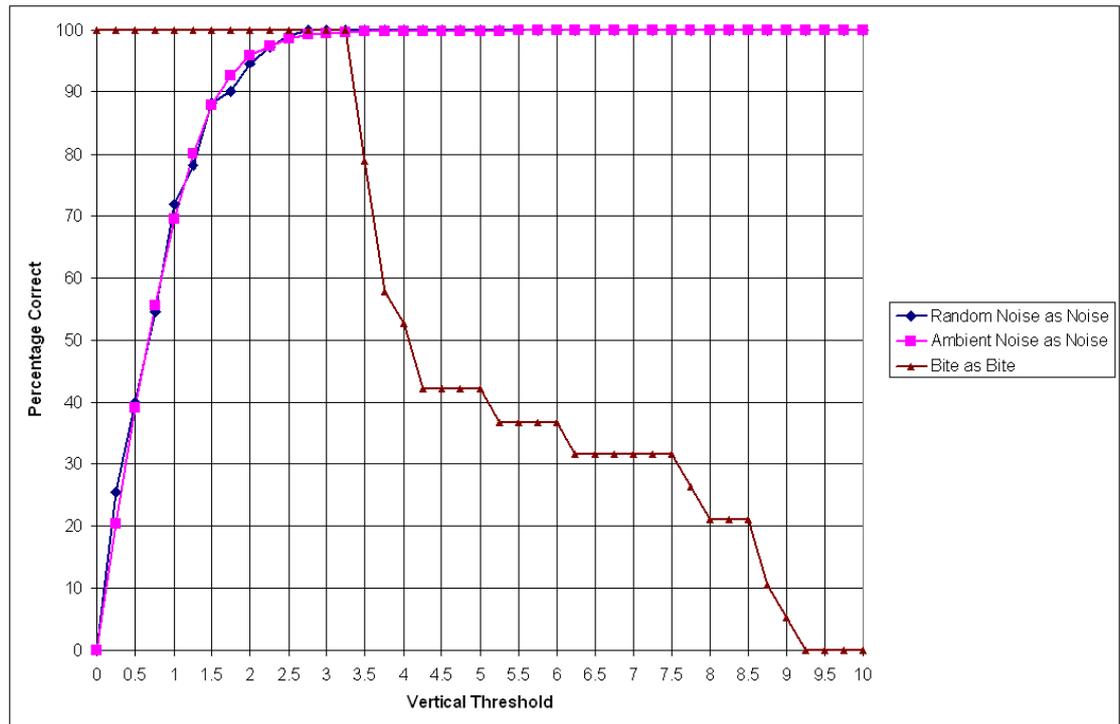
Figure 4.13: Detection of random noise, ambient noise and bites

It can be seen from the graph that in order to achieve no false detections in random and ambient noise a threshold of above 4 is required. The true negative detection in

ambient noise rate at a threshold of 3 is 99.56%; this figure suggests that the distribution of FD values has a normal distribution when the audio itself is normally distributed. At a threshold level of 3, all bites were sucessfully detected, however a small percentage of noise is falsely detected as bites. The ideal threshold level depends upon the needs of the user in terms of the relative importance of false negatives and false positives. The system being developed here is intended to be used alongside other larvae detection techniques which are currently used by DEFRA. Since part of the motivation for this work is the risk of false negative results from current techniques, a threshold of 3 was selected to minimise false negative results from this system.

4.2.7 Horizontal Threshold

Horizontal thresholding is applied in order to reduce the number of false positive results. A maximum event length, E_{MAX} is defined to prevent the detection of events which are too long to be attributed to the feeding of larvae. The value of E_{MAX} is dependant on the frame length selected and is a multiple of frame length.

4.2.8 Bite Padding

Since the detection method does not use any overlapping of frames it is necessary to expand the detect events at both ends to ensure that the acoustic activity is fully captured. Figure 4.14 shows the best and worst cases of frame positioning relative to the bite where the frame size is half of the bite duration. The original output from the vertical thresholding of frames is shown by the thick black line; each event is then expanded by the length of one frame at either end as shown by the thick red line. In the best case this results in the unnecessary expansion of the event to include noise; however this additional data should have no detrimental effect since it will be ignored by the species recognition method.
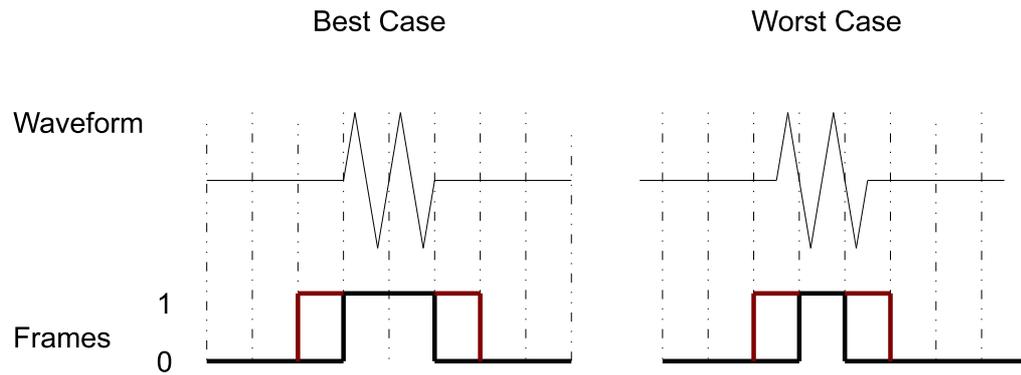
Figure 4.14: Event Expansion

4.2.9   Example Activity

Figure 4.15 shows the detection results for a recording of an unidentified larva over a long time period. This example shows how larval activity can vary over time; the period between 21:00 and 22:00 contains significantly less activity, for unknown reasons. The recording also appears to show that activity gradually increases at the start of the recording, this behaviour occurs in other recordings which have been made during this research and may indicate that larvae are sensitive to the movement and noise produced when attaching sensors.
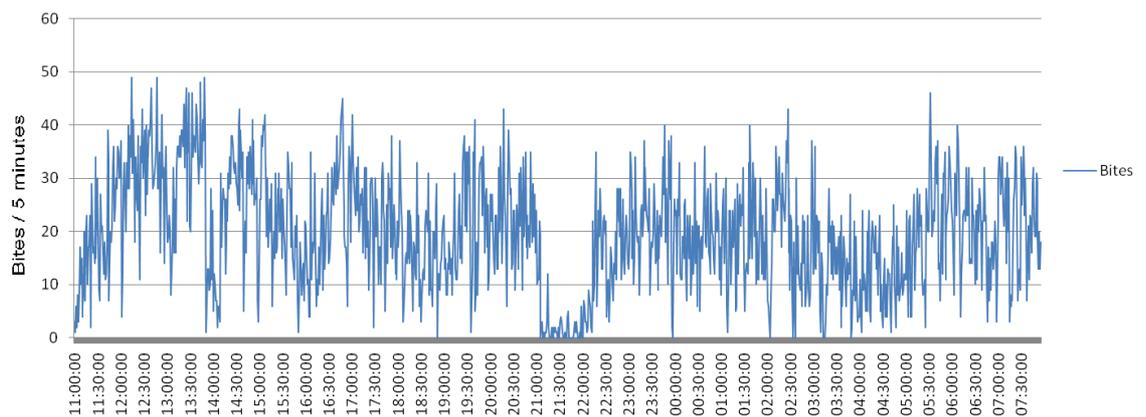
Figure 4.15: Activity of unknown larva over 20 hour period

4.3 Dual Sensor

False positive events cannot be eliminated entirely by means of horizontal and vertical thresholding. In recordings in a laboratory environment, false positives may be introduced by electrical switching noise for example. In field recordings sounds produced by external activity such as twigs breaking may be of short enough duration to trigger false events.

In order to further limit the number of false positive results produced a simple dual sensor technique was devised. Its implementation adds little additional computational or monetary cost to the system. Physically the secondary sensor is identical to the primary sensor and is connected to the spare channel on the USB audio device. This second sensor is used to detect ambient sound and is not attached to the sample material.

Fractal Dimension analysis is performed on the second channel in exactly the same way as on the primary channel. For each segment of audio data, two events lists are therefore produced. The events on the secondary channel are used to cancel any events which occur in the same position on the primary channel since it is likely that such events are not the result of larval feeding activity. The implementation of the dual sensor system is covered in greater detail in Chapter 6.

4.4 Summary

This chapter has covered the methods used to acoustically detect larvae. Recording and monitoring methods which have been used by others have been considered and two types of acoustic sensor have been investigated.

The computational methods which have been used for acoustic event detection have been reviewed and a new technique based upon Fractal Dimension (FD) analysis is introduced. The background to FD and methods which are used in its estimation have been described and the performance of FD detection and short time energy detection has been compared. FD detection has been shown to enable the detection of events at lower signal to noise ratios. Finally the vertical and horizontal thresholding process and the use of a secondary sensor for the reduction of false positive events has been described and results provided for varied detection threshold levels.

Chapter 5

Species Identification

The task of automated identification or pattern recognition has been applied to a wide range of problems using numerous diverse methods (Ripley, 1996), (Theodoridis and Koutroumbas, 2003). The terms are used to describe a process by which sets of input data are grouped based upon their similarities into user-defined or machine-created classes which can be used to represent some form of meaningful output category.

Despite the wide range of methods used, the task can usually be generalised as a processing having two distinct stages - feature extraction and classification. In it's simplist form, feature extraction is the selection of the most useful information from the input data. Classification is the process by which this information is placed into the most appropriate output category. Perhaps confusingly, the term classifcation is also often used to encompass the entire pattern recognition task (Brown and Miller, 2007), (Lee et al., 2003), (Waser et al., 2011).

This chapter covers these two stages of pattern recognition separately and investigates the approaches taken by others for the purpose of automated acoustic identification of beetles and other insects.

5.1 Feature extraction

Feature extraction is the first stage in the automated classification process. It is the means by which the most useful elements or features are selected from the input data for classification. An ideal feature extraction method will select those features which exhibit the

greatest variation between classes whilst maintaining the closest similarity within classes. The dimensionality of the input data will be reduced as features are extracted, by discarding input data, and generated, by combining data. This dimensionality reduction is important since a classifier will suffer if provided with excessively large dimension data as well as data with inadequate dimension. The process decreases the number of parameters which are used in the classifier, allowing better generalisation (Bishop, 1995). That is to say the classifier will have a greater ability to cope with variations of data which are within classes. There are also obvious computational benefits to dimensionality reduction, namely fewer calculations and a lower memory requirement for input data and classifier storage. The selection of a computationally efficient feature extraction technique is of particular importance to this project since it is necessary that classification is performed in real-time.

The remainder of this chapter will look at the various techniques which have been employed by others for use in the automated acoustic identification of beetles, animals and sound in general. In particular, the techniques used in DEFRA project PH0191 will be investigated. Table 5.1 lists feature extraction methods which have been used to analyse sounds produced by beetle larvae; the letters D and I in the task column represent Detection and Identification.

Species	Feature Extraction Method	Task	Reference
Rhynchophorus ferrugineus	Filterbank	D	(Pinhas et al., 2008)
Rhynchophorus ferrugineus	Short-time Fourier Transform & Discrete wavelet packet transform	D	(Potamitis et al., 2008)
Rhynchophorus ferrugineus	Time Frequency Distribution	D	(Al-Manie and Alkanhal, 2005)
Various species	Time Domain Signal Coding	I	(Farr, 2007)
Anoplophora glabripennis	Spectral Profile and Temporal Patterns	D	(Mankin et al., 2008)

Table 5.1: Feature extraction methods used in the analysis of beetle larvae sounds

5.1.1 Spectral Profiling

Mankin *et al.* used a frequency domain technique for the detection of Asian Longhorn Beetle larvae (Mankin et al., 2008). The feature extraction stage of the technique was spectral estimation by means of the Discrete Fourier Transform (DFT). The DFT is widely used for spectral analysis and is used to generate a power spectrum from a discrete signal, providing information on the relative power of different frequency components within the signal.

The DFT assumes that signals are circular, therefore care must be taken when selecting an appropriate windowing function to prevent the introduction of false frequency information. The Fast Fourier Transform (FFT) algorithm is commonly used because of its relative computational efficiency (Cooley and Tukey, 1965). It requires that the signal length is a power of two; shorter signals can be increased to the required length by zero padding.

5.1.2 Filterbank Analysis

Pinhas *et al.* used filterbank analysis for the feature extraction stage of an acoustic detection system for Red Palm Weevil (*Rhynchophorus ferrugineus*), acheiving up to 98.8% detection rates (Pinhas et al., 2008). Their technique involves first dividing the input signal into fixed lengthed frames with 50% overlap. After applying an amplitude threshold to discard frames which were considered to be noise, the DFT of each frame is calculated and a Hamming window applied.

Filterbanks are used to reduce the dimensionality of spectral data by smoothing and frequency selectivity. A set of band pass filters, which may vary in position and scale, are multiplied with the spectral data to produce an average energy value for each band (Bimbot et al., 2004). A commonly used filter bank technique is the Mel-frequency cepstrum (MFC) which leads to the generation of Mel-frequency cepstral coefficients (MFCCs). The spacing of filters is based upon the MEL scale, which was devised by Stevens and Volkman and is based upon the human perception of sound (Stevens et al., 1937). MFCCs are frequently used for the analysis of human speech and speaker recognition (Bimbot et al., 2004), (Kamruzzanman et al., 2007), (Viikki and Laurila, 1998).

5.1.3 Short Time Fourier Transform (STFT)

Al-Manie and Alkanhal used this time-frequency domain feature extraction technique for the detection of Red Palm Weevil (Al-Manie and Alkanhal, 2005). The paper does not list any detection results; however the method employed is commonly used in audio analysis and therefore is included here.

The STFT is used to produce a time-frequency distribution by first segmenting the signal into frames of fixed length using a windowing function to minimise the introduction of errors, then applying the DFT (Section 5.1.1) to each frame (Hlawatsch and Auger, 2008). The fixed resolution of the STFT is a limitation as there is a trade-off between frequency resolution and time resolution. Narrow frames allow for better time resolution at the expense of frequency resolution; wide windows provide better frequency resolution at the expense of time resolution. Additionally, for any signal there is a minimum window width for which meaningful frequency information can be generated (Cohen, 1995).

5.1.4 Fractal Dimension

The possibility of using fractal dimension (FD) values as a feature for bite species classification is considered here because these values are already calculated during the bite detection process described in Chapter 4. A species identification method which could use these values would be advantageous since the extra computing time required would be minimal.

To assess the suitability of discriminating between bites produced by different species by this method the FD values for a number bites from various beetle species were calculated. A histogram of these values can be seen in Figure 5.1. These results show a significant overlap between the ranges of FD values of bites; based upon this data it was concluded that fractal dimension values alone are not suitable for use in the separation of bite sounds produced by different beetle species.

5.1.5 Time Domain Signal Coding (TDSC)

Farr (2007) used a technique known as Time Domain Signal Coding (TDSC) for the feature extraction stage of an acoustic larvae identification system (Farr, 2007). This work differs from most of the other methods covered here in that it is used to perform iden-
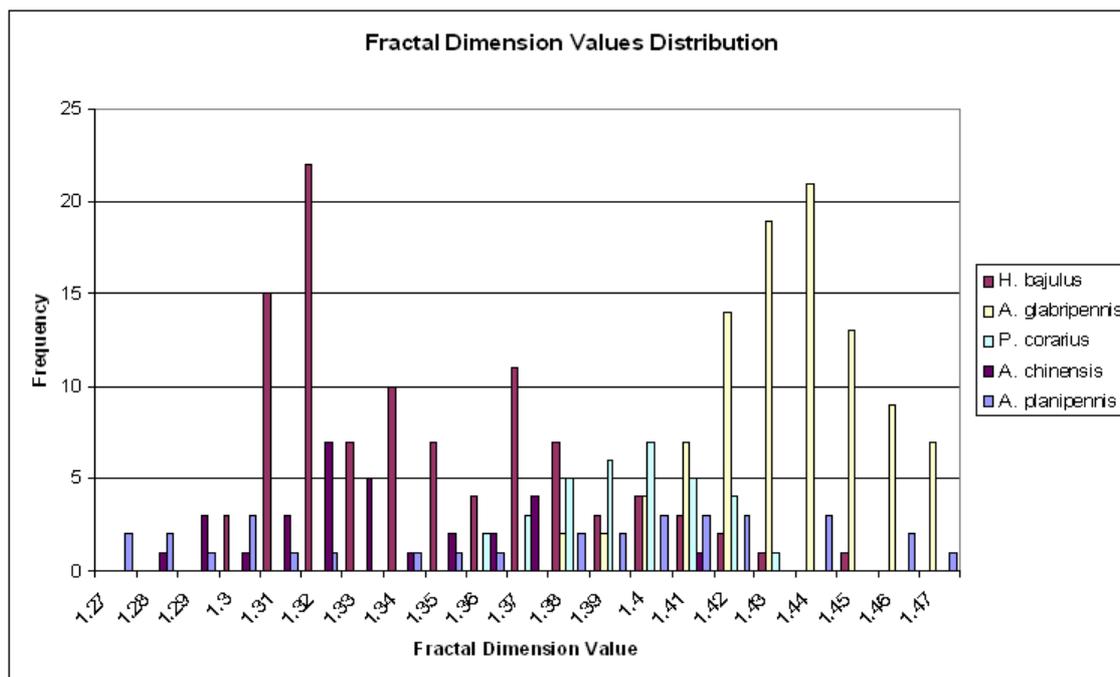
Figure 5.1: Distribution of FD Values

tification of species (classification between different species) rather than simply detection (classification between insect and noise).

The technique originates from a time domain method for the compression of speech data, Time Encoded Speech (TES) (King and Gosling, 1978). This was then developed into Time Encoded Signal Processing (TESPAR) by King some years later (King, 1995). TESPAR was first used in the analysis of insect sounds by Chesmore *et al.* (Chesmore et al., 1997).

Time Domain Signal Coding (TDSC) aims to represent the characteristics of a given waveform by its shape and duration values between successive zero crossings; termed an epoch. Shape values are calculated as the number of positive minima or negative maxima while duration is simply the number of samples between the given zero crossings. Figure 5.2 shows an example waveform with annotated TDSC calculations. The waveform can be seen to have two epochs, each encoded with shape and duration information. The first epoch is positive and contains a single minimum giving it a shape value of 1. The second is negative and contains two maxima, giving it a shape value of 2.

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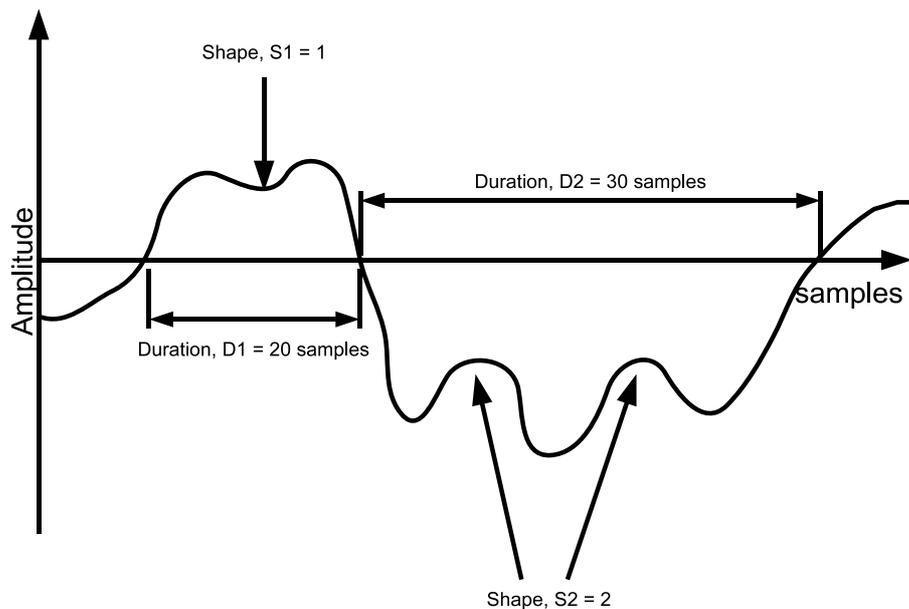
Figure 5.2: Example of waveform epochs (D1,S1) and (D2,S2)
Adapted from (Chesmore, 2001).

Shape and duration values are then combined to produce a single code value for each epoch within the waveform, either by using a code-book or equation. An example code-book is shown in Figure 5.3.

Fixed codebooks can be a limitation in TDSC since they may result in the failed encoding of certain complex waveform features, such as unusually high numbers of minima in an epoch, due to the lack of codes to represent them (Farr, 2007). Swarbrick attempted to overcome this limitation by introducing a technique which would select appropriate codebooks automatically (Swarbrick, 2001). Farr removed the need for the use of codebooks entirely by restricting the input signal with band-pass filtering and minimum and maximum duration limits such that codes could be generated using a single simple equation, equation 5.1 (Farr, 2007).

$$CODE = ((S * S_F) * D) \qquad (5.1)$$

In equation 5.1, S is shape value, D is duration value and S_F is a scaling factor determined

Duration	Shape				
	0	1	2	3	4
1	1				
2	2				
3	3				
4	4				
5-10	5	6			
11-14	7	8	9		
14-20	10	11	12	13	
20-25	14	15	16	17	18

Figure 5.3: Example codebook

from the input signal restrictions.

After epoch codes have been generated, either by the use of a code book or equation 5.1, the generation of features for the classifier is a simple process. For each waveform, the sequence of codes produced is used to generate a histogram showing the frequency of occurence of each code, producing a 1-dimensional S-matrix. Alternatively the frequency of occurence of successive pairs of codes, i and j, separated by a lag L, is used to produce a 2-dimensional histogram known as an A-matrix using equation 5.2.

$$a_{ij} = \frac{1}{(N-L)} \sum_{n=L+1}^{m=N} x_{ij}(n) \tag{5.2}$$

In equation 5.2, a_{ij} is element (i,j) of matrix A, L is lag, $x_{ij}(n) = 1$ if $t(n) = i$ and $t(n-L) = j$ (0 otherwise) and $t(n) = n$th symbol (Chesmore, 2001).

5.1.6 Selection of feature extraction method

A decision was taken to concentrate on the use of time domain feature extraction rather than frequency domain techniques for reasons which are outlined here. Firstly, time domain methods tend to be computationally simple whereas frequency domain and time-frequency domain methods are relatively computationally expensive due to the require-

ment of the calculation of fourier transforms (Chesmore, 2001). Signals produced by larvae feeding are very short, as discussed in Chapter 3, which may limit the meaningful information which can be extracted in the frequency domain, particularly if the signal is further segmented as is the case with the STFT. Finally, the results shown by Farr using TDSC show that this time-domain method is capable of extracting suitable features for species identification (Farr, 2007). The frequency and time-frequency domain techniques tend to be limited to the detection of larval bites from background noise rather than identification of species. There is little evidence to suggest that frequency domain feature extraction can be reliably applied to classification between species.

5.1.7 TDSC Limitations

TDSC has a number of potential limitations in terms of the features which it is able to encode. Two potentially useful features which are ignored in the encoding process are the relative amplitude of peaks and the positions of maxima and minima within epochs. To illustrate this, Figure 5.4 shows two visually different waveforms which have identical TDSC code and duration values in all epochs. TDSC is best suited to waveforms which exhibit a complex struture in terms of shapes per epoch such as Birdsong
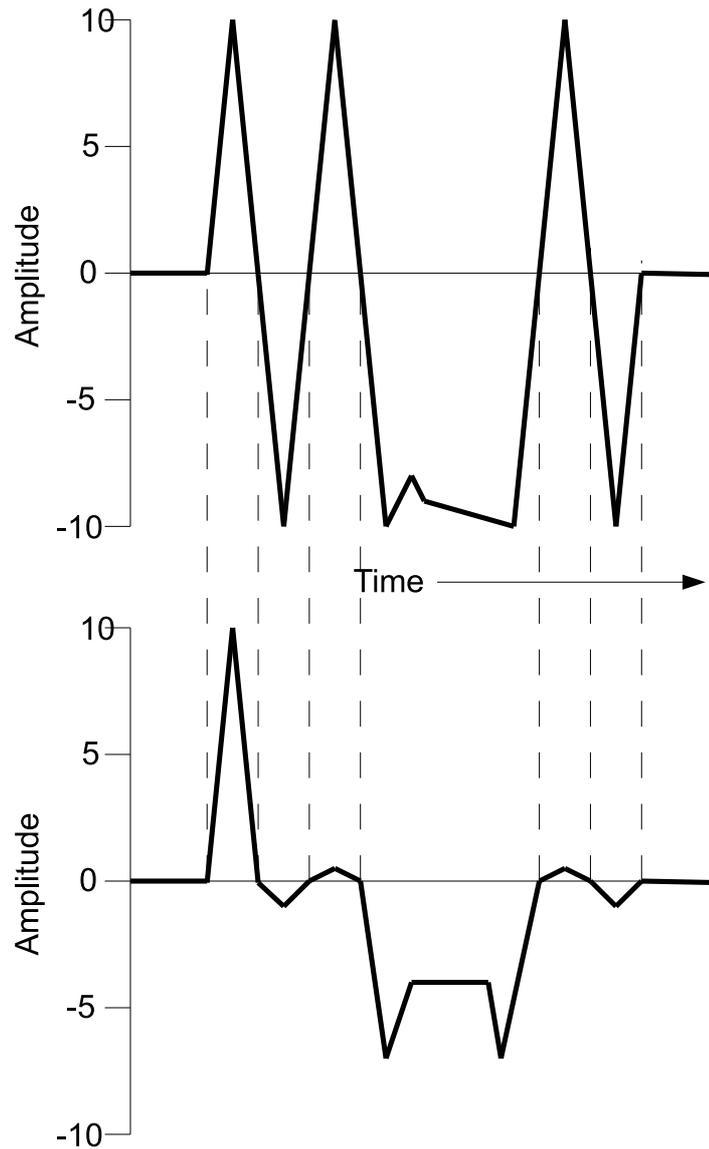
Figure 5.4: Two waveforms with identical TDSC encoding

In order to determine what information was being encoded by TDSC, the complexity of shapes in epochs of bite and noise events was analysed. This involved calculating the TDSC shapes for the epochs of a number of bites to determine the proportion containing useful information. Table 5.2 shows the percentage of epochs encoded with different shape values for *A. glabripennis* bite events. Over 79% of all epochs encoded have a shape value of zero; this means that the encoding process is in effect encoding purely the zero crosssing rate for these epochs.

Encoding Characteristic	Percentage
Epochs with shape 0	79.24%
Epochs with shape 0 or 1	91.05%
Bites entirely shape 0	0%
Bites entirely shape 0 or 1	6%

Table 5.2: *A. glabripennis* TDSC shape values

Table 5.3 shows the same shape encoding information but for *H. bajulus* bite events. In this case the proportion of zero shape encoded epochs is almost 98% and 32% of encoded bites contain no epochs with shape information.

Encoding Characteristic	Percentage
Epochs with shape 0	97.78%
Epochs with shape 0 or 1	99.04%
Bites entirely shape 0	32%
Bites entirely shape 0 or 1	79%

Table 5.3: *H. bajulus* TDSC shape values

Encoding Characteristic	Percentage
Epochs with shape 0	72.85%
Epochs with shape 0 or 1	84.71%
Bites entirely shape 0	1%
Bites entirely shape 0 or 1	1%

Table 5.4: Noise event TDSC shape values

The high proportion of epochs which have a TDSC shape value of zero suggests that shape may not be useful feature for species classification. Additionally it has been demonstrated above that a single shape value can represent very different waveform characteristics. The combination of these two factors and the lack of relative amplitude encoding in TDSC led to its rejection as a feature extraction method.

5.2 Relational Trees

It has been demonstrated that TDSC encoding often results in insufficient information being obtained from larval bite waveforms; an alternative time-domain encoding method using relational trees was investigated as it could potentially overcome some or all of the limitations of TDSC. The concept of the relational tree as a representation of waveforms was introduced by Ehrich and Foith (Ehrich and Foith, 1976). Their paper suggests a method which uses a tree structure to represent the relative positions of local minima and maxima within a waveform.

The encoding process converts the waveform representing a larval bite sound into a complete binary tree which holds information about the relative amplitudes and positions of various peaks from the waveform. In a complete binary tree all nodes have exactly two children down to a specified tree depth. Examples of complete and incomplete binary trees can be seen in Figure 5.2.
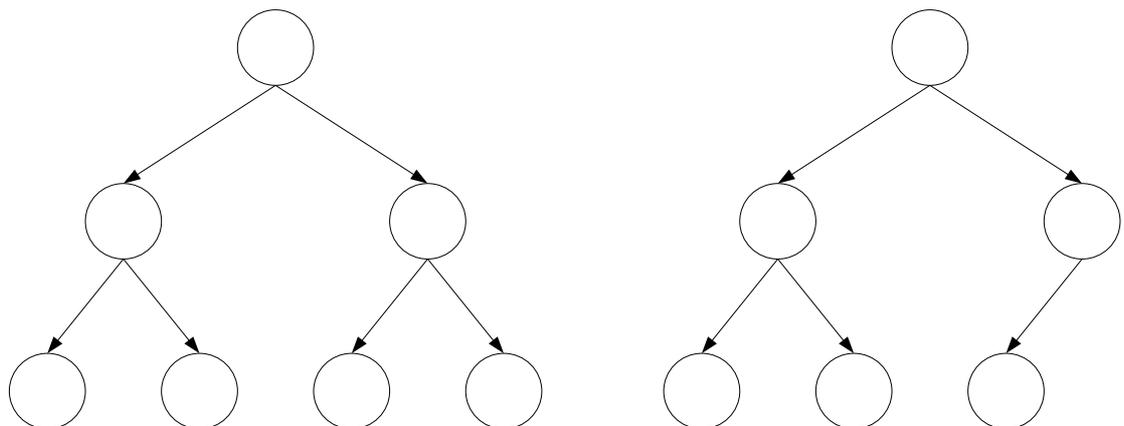
Figure 5.5: Complete (left) binary tree and incomplete (right) binary trees

5.2.1 Tree Generation

This section will explain the process by which a relational tree is generated from a waveform. The process can be used to generate a tree for a waveform of any size and the generated tree may have any number of nodes dependent on the selected tree depth.

1. Decide upon a maximum tree depth.

2. Look for the largest peak in the waveform.

3. Store the amplitude and position values of the peak as the base node of a tree.

4. Look for the largest peaks either side of the last peak.

5. Add the positions and amplitudes of these peaks as child nodes of the base node.

6. Repeat until the maximum tree depth is reached or until no further peaks can be found.

At this stage the binary tree which has been created may be incomplete due to the tree depth exceeding the number of peaks which need to be represented. Figure 5.6 shows an artificial example waveform with annotated amplitude and position values; the relational tree generated from this waveform is shown in Figure 5.7.
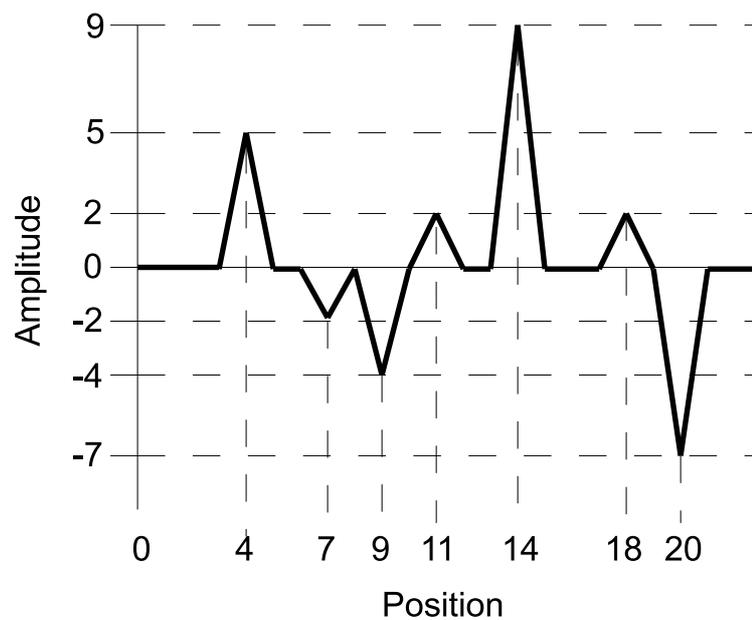
Figure 5.6: Example waveform
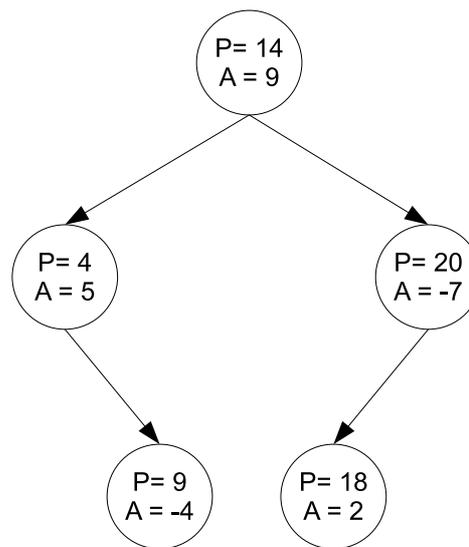
Figure 5.7: Example relational tree (Depth 3)

5.2.2 Tree Normalisation and Completion

The extraction process used by the bite detection method means that a bite will not necessary occur centrally within the segment of audio which encompasses it. The detected audio segment may be one of several discrete lengths depending on how many fractal frames are required to represent it (see Chapter 4). The classifier requires input features which are dependent on neither of these two factors so the values are first normalised. In order to change node values to make them relative to the base node, the position value of the base node is subtracted from all node position values (equation 5.3). The amplitude value, A, of each node, x, is calculated as a signed percentage of the base node's amplitude using equation 5.4 where r is the root node. This step is necessary since the absolute amplitude has no meaning in the context of classification.

$$P_x{}^N = P_r - P_x \qquad (5.3)$$

$$A_x{}^N = \frac{A_x * 100}{A_r} \qquad (5.4)$$

After normalisation the tree is completed by adding nodes with amplitude and posi-

tion values of zero to any empty node positions within the maximum tree depth. The normalised and completed version of the relational tree in the previous section can be seen in Figure 5.8.
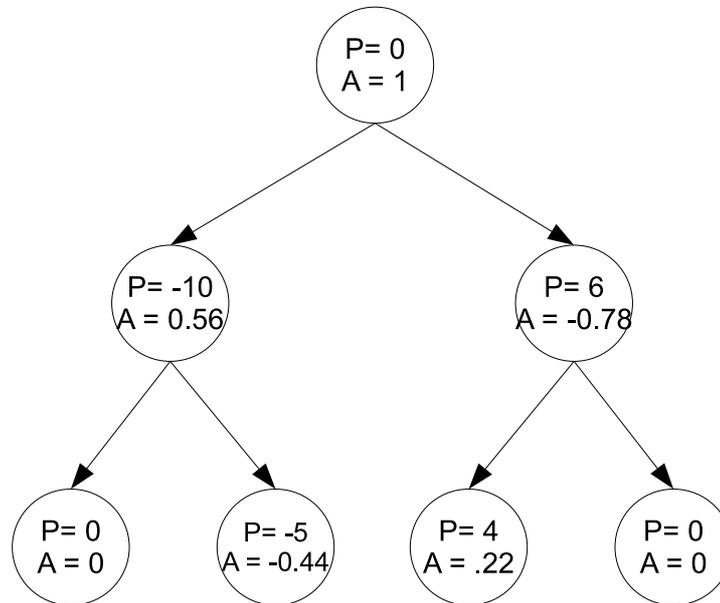
Figure 5.8: Normalised relational tree (Depth 3)

5.2.3 Tree Quantisation

The amplitude values stored in the relational trees are quantised to 200 levels. This in effect means that the values are stored as a signed integer representation of the percentage of the largest amplitude value. This quantisation has the effect of limiting the influence of low amplitude peaks which may be encoded when the tree depth is large. The variation of quantisation levels and it's impact on classification is discussed later in this chapter. Position values are not quantised since there is no upper limit to the relative position of any peak in the waveform.

5.2.4 Tree Serialisation

In order to present the relational tree data to a classifier it must first be serialised. This process converts a relational tree representation of a waveform into a single array of input features. Since the tree generation process ensures that all trees are complete, the seri-

alisation process will result in the production of a consistent number of features which is related to the depth to which the tree has been generated. The number of nodes, n, in a complete binary tree can be calculated from the tree depth, d, using equation 5.5.

$$n = 2^d - 1 \tag{5.5}$$

Since the data stored within the relational trees is relative to the largest peak within the waveform, stored in the base node, this node need not be serialised as it will always contain the same values. Taking this into account and adjusting for each node containing two pieces of data, amplitude and position, the number of features, F, in a serialised tree can be calculated from the tree depth, d, using equation 5.6.

$$F = 2 * (2^d - 2) \tag{5.6}$$

The serialisation process operates depth first, thus the relational tree shown in Figure 5.9 is converted to the data row shown in table 5.5 where P_n and A_n represent the position and amplitude values of node n.
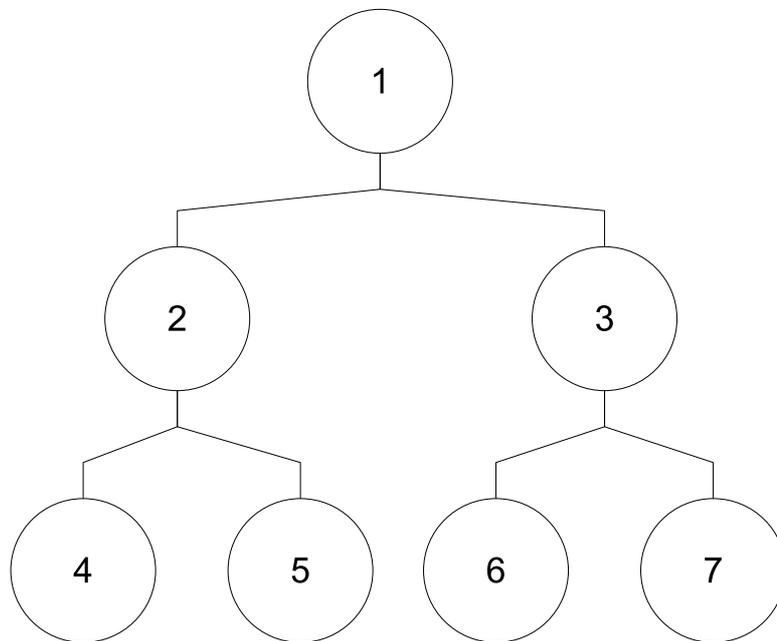
Figure 5.9: Example relational tree with numbered nodes

Feature	1	2	3	4	5	6	7	8	9	10	11	12
Node	2		4		5		3		6		7	
Data	P_2	A_2	P_4	A_4	P_5	A_5	P_3	A_3	P_6	A_6	P_7	A_7

Table 5.5: Serialised Relational Tree Values

5.2.5   Bite Data Compression

If bites can be sufficiently represented in relational tree format using a tree depth of 4 using 10 amplitude quantization levels and assuming a maximum bite length of 1024 samples (at 44.1kHz), each bite can be represented using 56 bytes of data. This represents a compression ratio of 0.0034 against the original audio data.

This compression may be useful if the system were extended to using large numbers of wirelessly linked sensors since bite classification could be performed at a central unit which could receive bite feature information using low bandwidth communication.

5.2.6   Algorithm & Computational Complexity

5.3   Classification

5.3.1   Artificial Neural Networks

Artificial Neural Networks (ANNs) have been widely used to classify sounds produced by animals and insects in particular and the term ANN covers a wide range of different techniques. Table 5.6 provides a list of some of these applications and the type of ANN used in each case.

Application	ANN	Reference
Birdsong recognition	MLP	(McIlraith and Card, 1995)
Fish School Identification	MLP	(Haralabous and Georgakarakos, 1996)
Orthoptera Identification	MLP	(Chesmore, 2001)
Beetle Species Identification	MLP, LVQ	(Farr, 2007)
Bat Species Identification	MLP	(Parsons and Jones, 2000)
Fish Species Identification	MLP, SOM	(Cabreira et al., 2009)

Table 5.6: Applications of ANN to animal sound classification

They are also commonly applied to the classification of time-domain features of other audio data as can be seen in table 5.7.

ANNs were used here due to their frequent use in animal sound recognition, particularly when dealing with time domain features. The project which preceded this work, undertaken by Farr, used MLP and LVQ networks in combination with TDSC (Farr, 2007). As a result, one of the objectives of this project was to investigate these techniques further. Whilst relational trees are being used in place of TDSC, the time domain features extracted are similar and MLP and LVQ networks were selected to provide a comparision with previous work.

Application	Feature	ANN	Reference
Speech Recognition	ZCR	MLP	(Paul and Parekh, 2011)
Speech Recognition	ZCR, p-p amplitude, DFT	MLP	(Cole and Fanty, 1990)
Speaker Recognition	ZCR, peak amplitude	MLP	(Jeong et al., 2000)
Vehicle Recognition	Log Energy, TDSC	LVQ	(Evans, 2010)
Vehicle Recognition	TESPAR	SOM	(Mazarakis and Avaritsiotis, 2007)
Bird Species Indentification	TDSC	MLP	(Chesmore, 2001)

Table 5.7: Applications of ANN to time domain feature classification

5.3.1.1   Principles of ANNs

Artificial Neural Networks provide a decision making structure which is loosely based upon that of the human brain. The are commonly applied to pattern recognition tasks where data must be classified or clustered into groups based upon similarities in its features (Bishop, 1995).

The most basic element of an ANN is called the perceptron and was devised by Rosenblatt (Rosenblatt, 1962). The simplist form of perceptron is a transfer function where a single scalar input, ϕ, having weight, w, is summed together with a bias, b, and passed

through an activation function, g. This perceptron is illustrated in Figure 5.10 and can be represented using equation 5.7.
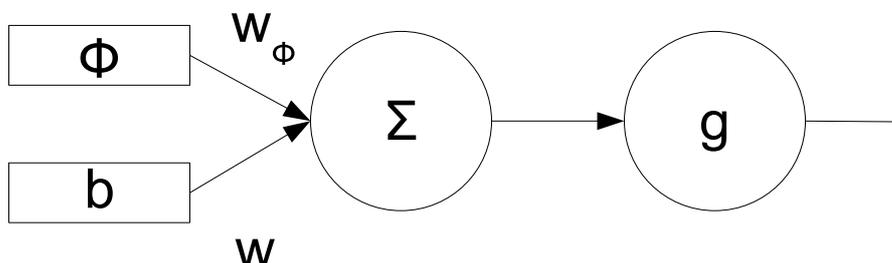
Figure 5.10: Perceptron with single input

$$y = g(\phi w + bw) \tag{5.7}$$

The activation function, g, may take one of several forms; a commonly used example is provided in equation 5.8 (Bishop, 1995).

$$g(a) = \begin{matrix} -1 \; when \; a \; <0 \\ +1 \; when \; a \; \geq 0 \end{matrix} \tag{5.8}$$

A perceptron with only a single single input is of very little practical use; in practice perceptrons have a vector input, ϕ, each having its own weight, w. The ouptut of the perceptron is therefore the sum of all weighted inputs and the weighted bias, b_w, with the chosen activation function applied. For an input vector ϕ_j, of length N, the output is given by equation 5.9 and is represented by Figure 5.11.

$$y = g((\sum_{j=0}^{N} w_j \phi_j) + b_w) \tag{5.9}$$
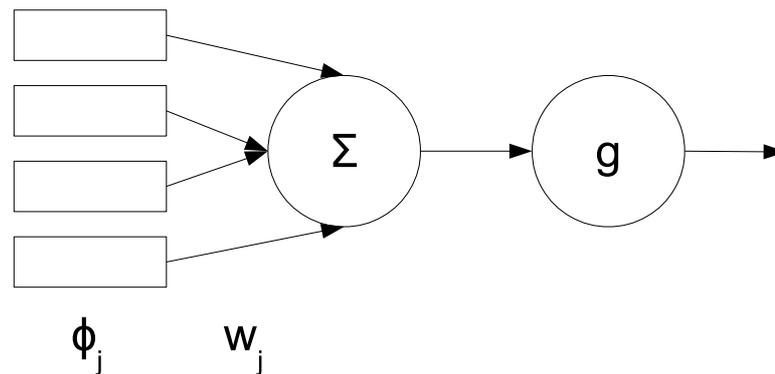
Figure 5.11: Perceptron with vector input

It is widely recognised that single layer ANNs such as that shown in Figure 5.11 are only capable of solving linearly separable problems and therefore have limited practical use in many pattern recognition tasks (Bishop, 1995), (Heaton, 2005), (Elizondo, 2006). Figure 5.12 shows linearly separable data on the left and non-linearly separable data on the right.
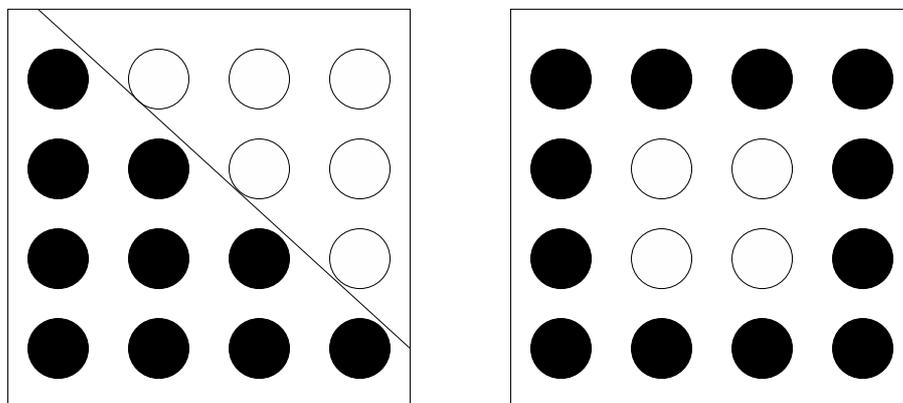
Figure 5.12: Linear Separability

The solution to this limitation is to use multiple layers of interconnected perceptrons; approaches tend to include one or more layers between the input and output layer, termed 'hidden' layers. It has been shown that any continuous function can be represented using a single hidden layer (Cybenko, 1989). This form of ANN is termed the Multiple Layer

Perceptron (MLP), and is illustrated in Figure 5.13.
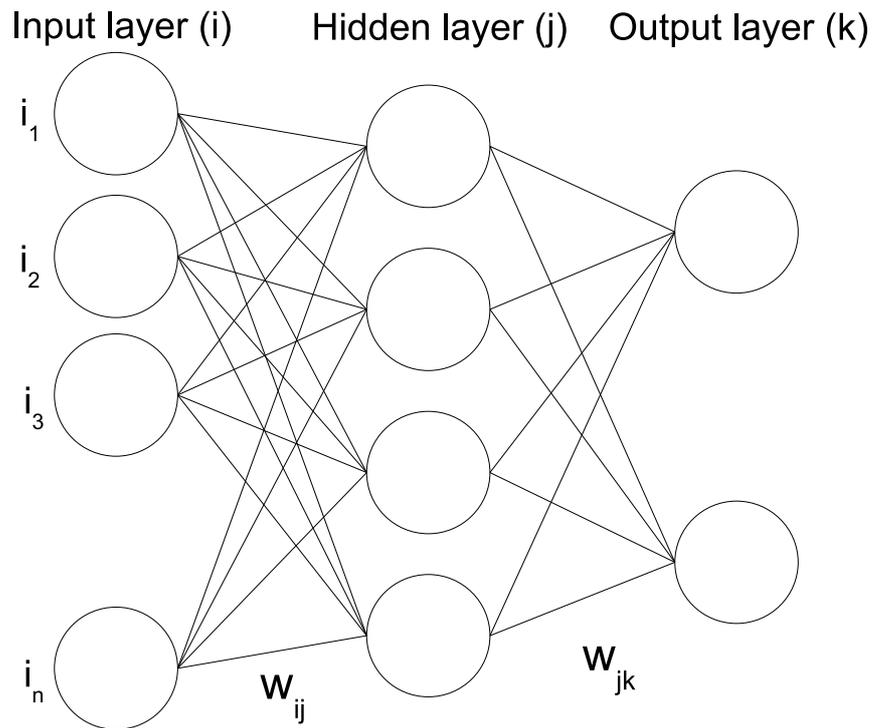
Figure 5.13: Multiple Layer Perceptron Network

The network has an input vector, i, having length n which provides a weighted input, w_{ij}, to a hidden layer, j. The output of the neurons in the hidden layer provide weighted inputs, with weights w_{jk}, to an output layer, k. The number of nodes in the input layer relates to the number of features provided by the feature extraction method; the number in the output layer corresponds to the number of desired output classes. The hidden layer may contain any number of nodes depending on the requirements of the network and need not match the size of either the input or output layers (Farr, 2007).

5.3.1.2   Training

Training is the process by which the weights of inputs to nodes in the ANN are adjusted in order for the network to solve the problem presented to it. The methods can be divided into two categories, supervised and unsupervised learning.

Supervised learning is commonly, but not exclusively, used to train networks for classification. The generalised aim of classification is to separate data into pre-defined output

classes; in the case of this research the output classes represent species of beetle. The supervised learning process uses a set of training data for which the desired output class is known, to iteratively adjust the weights of inputs to neurons in order to minimise the classification error; a popular example is the back-propagation method, devised by Bryson and Ho (Bryson and Ho, 1969). The back propagation algorithm consists of a number of repeated steps; firstly the input vector is propagated forward through the network to produce an output vector. The error is then calculated for each output unit based upon the actual and desired output vectors. The error is then propagated backwards through the network and used to adjust weights such that the error decreases.

5.3.1.3 Self Organising Maps

Unsupervised learning can be used to train both clustering and classification systems. The generalised aim of clustering is to group data based upon its similarities without the use of pre-determined output classes. A widely used unsupervised network is the self organising map (SOM) which was devised by Kohonen (Kohonen, 1982). The SOM represents input vectors by points on a grid, which is usually 2-dimensional (Bishop, 1995); this structure is shown in Figure 5.14. Each output unit is connected to each input node in the vector $\underline{x}$ using a weight vector w_{ij}, where (i,j) is the location of the unit (Jain et al., 1996).
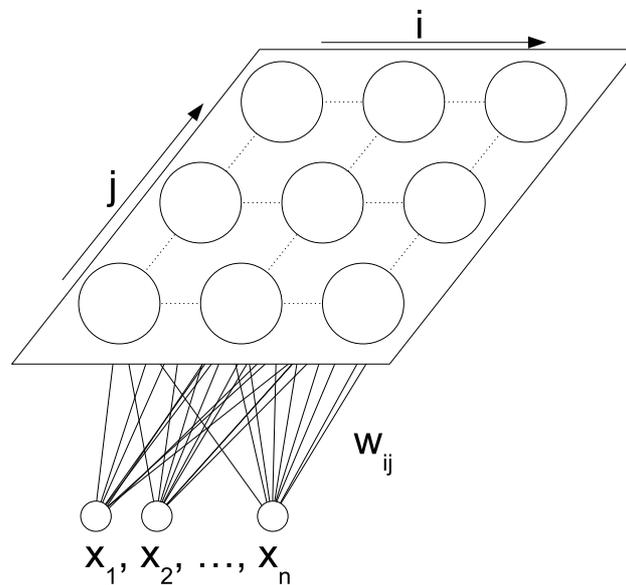
Figure 5.14: Self Organising Map

The learning algorithm begins by initialising all weights to random numbers. An input vector is then selected at random from the data set and the distance from this vector to all weight vectors is calculated. The Euclidean distance is commonly used and can be calculated using equation 5.10, where y_{ij} is the distance to the unit at location (i,j) and n is the number of dimensions in the input vector.

$$y_{ij} = \sqrt{\sum_{d=0}^{n}(x_d - (w_{ij})_d)^2} \tag{5.10}$$

The winning or best matching unit is that which has the minimum distance to the input vector. This unit is then used to calculate the neighbourhood of units which will have their weights adjusted. A neighbourhood function decreases the neigbourhood size with each training iteration, allowing the network to converge. The weights of units within the neighbourhood are than updated using the rule shown in equation 5.11.

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(t)[x(t) - w_{ij}(t)] \tag{5.11}$$

$\alpha(t)$ is the learning rate which is used to control the impact that input vectors have on unit weights as training progresses; this value decreases with each iteration.

5.3.1.4   Learning Vector Quantization

Learning Vector Quantization (LVQ) is an ANN structure and training method which combines elements of both supervised and unsupervised learning (Kohonen, 1990). This is achieved by using two layers of neurons; an unsupervised layer which operates in similar way to a SOM and clusters input vectors into sub-classes, and a linear layer which classifies sub-classes into pre-defined output classes in a supervised manner.
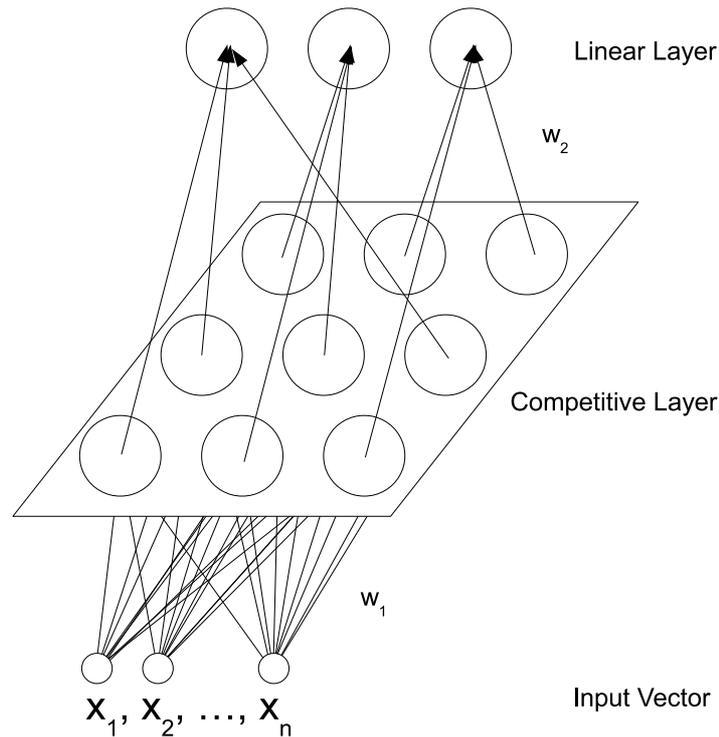
Figure 5.15: LVQ Network

The network has two sets of weights; these are shown as w_1 and w_2 in figure 5.15. w_1 weights connect input features to units in the competitive layer as with the SOM network. w_2 weights are used to map sub-classes to output classes.

In each training iteration an input vector is chosen and the best matching unit in the competitive layer is calculated using equation 5.10. The output of this unit to the linear layer is 1; all other competitive layer units will have output 0. If the input vector has been classified correctly then the weight vector of the best matching unit is moved towards the input vector using eqaution 5.12.

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(t)[x(t) - w_{ij}(t)] \qquad (5.12)$$

If the input vector has been classified incorrectly then the weight vector of the best matching unit is moved away from the input vector using equation 5.13.

$$w_{ij}(t+1) = w_{ij}(t) - \alpha(t)[x(t) - w_{ij}(t)] \qquad (5.13)$$

Various versions of LVQ exist (LVQ2, LVQ3) which attempt to overcome limitations in the original LVQ algorithm (Kohonen, 1989), (Kohonen, 1995). However, a recent analysis of various versions of LVQ has suggested that the original method outperforms other varients (Ghosh et al., 2006).

MLP networks trained with back propagation, and LVQ networks have been suggested to be the most commonly used learning methods in pattern recognition (Frasconi et al., 1997). Both MLP and LVQ have been sucessfully applied to several acoustic insect recognition tasks and will be studied further.

5.3.1.5 Dimensionality

The term 'Curse of Dimensionality' is often used to refer to problems encountered in using high dimensional data. It was devised by Bellman and describes the exponential growth of hypervolumes as a function of their dimension (Bellman, 1961). In neural networks this means that the size of the training data set required to accurately train a network increases exponentially with the dimensionality of the data.

In section 5.3.2.5 an MLP network is trained using data with dimensions varying between 6 (for a tree depth of 2) to 126 (for a tree depth of 6). Whilst classification rates increase when the data dimension is increased from 6 to 28, the small size of the data set means that the larger network may in fact represent the data classes less well. A large number of input features can lead to poor classifier generalisation if features are associated with noise. Since the data set size is small, the network may be over representing irrelevent portions of the input space.

5.3.2 Results

5.3.2.1 Neural Network Parameters

The MLP networks used have three layers: input, hidden and output. The number of neurons in the hidden layer varies the number of input features and output classes and is calculated using the equation given in section 5.3.2.5. The number of neurons in the output layer is equal to the number of output classes. The value of each neuron's output is continuously variable and uses a unipolor sigmoid activation function. In each test the network was trained through 500 iterations and a learning rate of 0.3 was used.

In the case of the LVQ networks, the number of units in the competitive layer varied between 20 and 50. In each test the network was trained through 1000 iterations; an initial learning rate of 0.1 and a linear decay learning function was used.

5.3.2.2 Data Sets

The two species of most interest to this project are *A. glabripennis* and *A. chinensis* (See Chapters 2 & 3). Given the high quarantine status of these species, opportunities for recording them are limited particularly since FERA did not obtain a licence for keeping these species in its laboratories in York until the final year of this research when *A. glabripennis* larvae were imported from France and several recordings of their feeding were made. No opportunity has arisen to record any significant quantity of *A. chinensis* feeding; therefore a substitute species, *Hylotrupes bajulus* has been used here. *H. bajulus* is a wood-boring species native to the United Kingdom which is considered a pest as it damages wood in buildings.

The *A. glabripennis* data set consists of 100 bites manually extracted from a number of different recordings which are listed in Table 5.8.

Description	Number of bites
Larva in live Acer, FERA, York 25th June 2010	34
Recording provided by FERA, March 2011	33
Recording provided by Massimo Faccoli (Italy), early 2011	33

Table 5.8: *Anoplophora glabripennis* recordings

The *H. bajulus* set consists of 100 bites manually extracted from a recording made by Farr during the previous DEFRA project, '2005_06_30 CSL 30 June 2005 Hylotrupes Bajulus Block 005A 002.wav' (Farr, 2007). The noise data set consists of 100 noise segments extracted from recordings made in environments with no larvae present.

The *A. planipennis* set consists of 50 bites extracted from a recording provided by the Canadian Food Inspection Agency which was made in an outdoor quarantine environment.

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5.3.2.3   Generation of test data

Relational tree features were generated using custom software written in C♯. The inputs to the software are bite audio data in the form of individual wave files which are grouped into folders which represent species classes; and two parameters which define the tree depth and amplitude quantization. The output of this software is a table of feature vectors formatted as a comma separated variable file which contains rows which represent each input file and columns containing the feature vector and class identifier.

5.3.2.4   Cross Validation

The classification process was tested using Weka version 3.64 which is a data mining tool implementing several machine learning techniques (Hall et al., 2009). MLP and LVQ networks were testing using cross validation which is a method which avoids the need to separate input data into a training and validation set. Data is divided into S segments and the network trained using $S - 1$ of these segments; the unused segment is then used to test the performance of the network (Stone, 1974). This process is repeated for all S segments such that each is used for testing once and the classification error averaged across S results. 10 segments were used for cross validation in all of the classification results presented in this chapter.

5.3.2.5   Tree Depth Variation

An initial tree generation depth of four was selected and the largest number of amplitude quantization levels (200) used. This produces an input vector consisting of 28 features. The classification results of an MLP network with a single hidden layer of 15 neurons can be seen in table 5.9 and correspond to an overall accuracy of 91.5%. The number of hidden layer neurons uses the WEKA default calculation of $n = (input features + output classes)/2$.

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	90	10
H. bajulus	7	93
Confidence	0.928	0.903

Table 5.9: *A. glabripennis* vs. *H. bajulus* confusion matrix (Tree depth 4)

The depth of the tree generation was then varied and the classification process repeated using the same set of data. The individual classification results can be seen in tables 5.10 to 5.13 and a summary in table 5.14.

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	88	12
H. bajulus	18	82
Confidence	0.815	0.872

Table 5.10: *A. glabripennis* vs. *H. bajulus* (Tree depth 2)

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	93	7
H. bajulus	11	89
Confidence	0.894	0.927

Table 5.11: *A. glabripennis* vs. *H. bajulus* (Tree depth 3)

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	86	14
H. bajulus	10	90
Confidence	0.896	0.865

Table 5.12: *A. glabripennis* vs. *H. bajulus* (Tree depth 5)

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	83	17
H. bajulus	9	91
Confidence	0.912	0.852

Table 5.13: *A. glabripennis* vs. *H. bajulus* (Tree depth 6)

Tree Depth	Accuracy
2	85%
3	91%
4	91.5%
5	88%
6	87%

Table 5.14: *A. glabripennis* vs. *H. bajulus* Summary

As could be expected, performance decreases when a very shallow tree depth is used. In this case the feature vector is too short and does not adequately represent the waveform. The performance also decreases for very high values on tree depth which is perhaps due to a larger proportion of features representing peaks which form parts of background noise, leading to poor generalisation in the classifier. The results suggest that the optimum tree depth is 4 layers.

5.3.2.6   Quantising amplitude values

One of the reasons for the selection of relational trees as a feature extraction method was the ability to encode relative amplitude values. A set of tests was run in which the number of quantization levels was varied, ultimately down to a single level to remove the feature entirely, to determine whether relative amplitude information provides any advantage to the classifier. The reduction in quantization levels is also potentially of interest since it may allow the classifier to perform better at generalisation.

Figure 5.16 shows the classification results plotted against the number of amplitude quantization levels using the same input data as the previous tests and a tree depth of 4.

This was repeated with the addition of a noise data class to produce the graph shown in Figure 5.17. The full classification results of these tests can be seen in Appendix C.
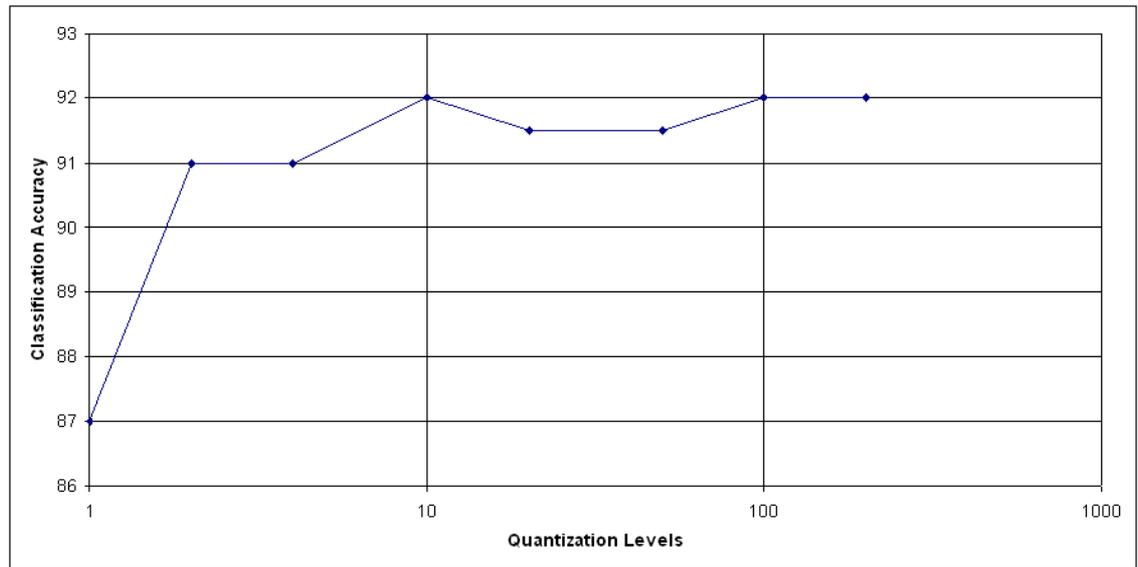
Figure 5.16: Effect of quantization on *A. glabripennis* vs *H. bajulus* classification
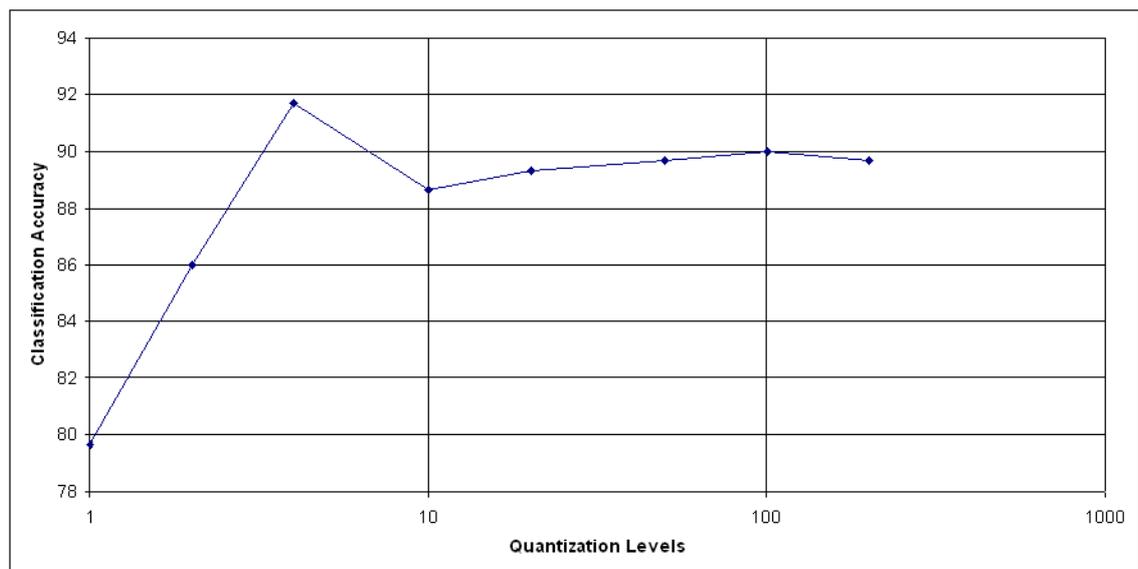
Figure 5.17: Effect of quantization on *A. glabripennis* vs *H. bajulus* vs Noise classification

In classifying *A. glabripennis* and *H. bajulus* the peak classification accuracy is 92% and is acheivable with 10 quantization levels. When no amplitude information is supplied as a feature the accuracy decreases to 87%, showing that amplitude information does improve classification. In classifying the two beetle species and noise the peak classification

accuracy, 91.67%, is acheived with 4 quantization levels and is significantly better than the accuracy acheived when no amplitude information is used, at 79.67%.

5.3.2.7 LVQ vs. MLP

The results presented in the previous section all used an MLP neural network. In this section the relative performance of LVQ and MLP networks is assessed.

LVQ classification between *A. glabripennis* and *H. bajulus* was first tested using 10 quantization levels and a tree depth of 4; the results can be see in Tables 5.15 to 5.18. The number of LVQ first layer nodes is was varied from 20 to 50.

Classified as →	*A. glabripennis*	*H. bajulus*
A. glabripennis	92	8
H. bajulus	6	94
Confidence	0.939	0.922

Table 5.15: *A. glabripennis* vs. *H. bajulus* LVQ Results (20 first layer nodes)

Classified as →	*A. glabripennis*	*H. bajulus*
A. glabripennis	89	11
H. bajulus	3	97
Confidence	0.967	0.898

Table 5.16: *A. glabripennis* vs. *H. bajulus* LVQ Results (30 first layer nodes)

Classified as →	*A. glabripennis*	*H. bajulus*
A. glabripennis	93	7
H. bajulus	5	95
Confidence	0.949	0.931

Table 5.17: *A. glabripennis* vs. *H. bajulus* LVQ Results (40 first layer nodes)

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	97	3
H. bajulus	4	96
Confidence	0.960	0.970

Table 5.18: *A. glabripennis* vs. *H. bajulus* LVQ Results (50 first layer nodes)

The results show that when 50 first layer nodes are used 96.5% of bites are correctly classified, significantly higher than the 92% acheived using MLP.

Tables 5.19 to 5.22 show the results of classification between *A. glabripennis*, *H. bajulus* and noise using LVQ. Again the number of first layer nodes is varied between 20 and 50. When using 50 first layer nodes, LVQ performs better than MLP, correctly classifying 95.6% of inputs as opposed to 88.67% with MLP.

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	97	3	0
H. bajulus	4	94	3
Noise	7	4	88
Confidence	0.898	0.931	0.967

Table 5.19: *A. glabripennis* vs. *H. bajulus* vs. Noise LVQ Results (20 first layer nodes)

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	95	5	0
H. bajulus	2	96	3
Noise	5	4	90
Confidence	0.931	0.914	0.968

Table 5.20: *A. glabripennis* vs. *H. bajulus* vs. Noise LVQ Results (30 first layer nodes)

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	98	2	0
H. bajulus	2	97	2
Noise	4	4	91
Confidence	0.942	0.942	0.978

Table 5.21: *A. glabripennis* vs. *H. bajulus* vs. Noise LVQ Results (40 first layer nodes)

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	98	2	0
H. bajulus	2	92	2
Noise	4	3	92
Confidence	0.942	0.951	0.979

Table 5.22: *A. glabripennis* vs. *H. bajulus* vs. Noise LVQ Results (50 first layer nodes)

A final comparison between MLP and LVQ treated both species as a single class to determine the performance of both classifiers at identifying bites from noise. The classification results for MLP are shown in Table 5.23. LVQ results are shown in Tables 5.24 to 5.27.

Classified as →	Bite	Noise
Bite	196	5
Noise	8	91
Confidence	0.961	0.948

Table 5.23: Bite vs. Noise MLP Results

Classified as →	Bite	Noise
Bite	196	4
Noise	14	85
Confidence	0.933	0.955

Table 5.24: Bite vs. Noise LVQ Results (20 first layer nodes)

Classified as →	Bite	Noise
Bite	196	4
Noise	10	89
Confidence	0.951	0.957

Table 5.25: Bite vs. Noise LVQ Results (30 first layer nodes)

Classified as →	Bite	Noise
Bite	196	4
Noise	8	91
Confidence	0.961	0.958

Table 5.26: Bite vs. Noise LVQ Results (40 first layer nodes)

When using 50 first layer nodes, LVQ again outperforms MLP although the difference is less than in the other classification tests. LVQ correctly classifies 96.66% of inputs whereas MLP only correctly classifies 95.67%.

Classification between three species, *A. glabripennis*, *H. bajulus* and *A. planipennis*, using LVQ was acheived with a lower overall success rate of 88.8%. The full results can be see in Table 5.28.

Classified as →	*A. glabripennis*	*A. planipennis*	*H. bajulus*
A. glabripennis	92	4	4
A. planipennis	7	37	6
H. bajulus	2	5	93

Table 5.28: *A. glabripennis* vs. *A. planipennis* vs. *H. bajulus* LVQ Results (50 first layer nodes)

5.3.3   Classification of Unknowns

The classification methods adopted appear to perform well in distinguishing between a small number of species but are not ideally suited to the detection of unknown inputs. Unknowns may either be associated with a species for which the network has not been trained, or with non-larvae sourced sounds such as those categorised as 'Noise' in tables

Classified as →	Bite	Noise
Bite	197	3
Noise	7	92
Confidence	0.966	0.968

Table 5.27: Bite vs. Noise LVQ Results (50 first layer nodes)

5.19 to 5.27.

In a real-world environment the system is likely to encounter a wide range of 'unknown' inputs which the neural networks adopted here could not be trained for since their features may be significantly different. The ability of the system to deal with unknown inputs may be necessary if the possible inputs cannot be limited by noise filtering and prior knowledge of potential species. In this case a the use of a different classification method may be more suitable.

5.4 Summary

This chapter has covered the species identification stage of the system. Several approaches to feature extraction which have been used in the analysis of insect sounds have been discussed. A novel approach to extracting larval bite features, relational tree generation, has been introduced.

The performance of two ANNs, MLP and LVQ, in classifying bites between two beetle species and between bite and noise has been tested. The LVQ network has been found to outperform MLP in each test case; classifying between *A. glabripennis* and *H. bajulus* with 96.5% accuracy.

Chapter 6

System Implementation

This chapter covers the implementation of the larvae detection and identification techniques described in the previous two chapters into a field deployable system for use by PHSI and FC PHS inspectors. It begins by considering the implicit and explicit requirements for the detection system based upon the information provided by DEFRA in the project proposal document and communication with PHSI inspectors who could potentially use the system.

Section 6.2 details the methods used to manually record the activity of larvae before the implementation of the automated system for the purpose of sensor testing and the building of a larger library of larvae recordings. The hardware implementation of the system is covered in section 6.3; this is separated into sensor design and implementation and the selection of PC hardware. The software implementation is then covered in section 6.4 and is primarily described from the point of view of the features available rather than being a full implementation report containing all of the underlying processes and code, which are explained to a very limited extent.

The chapter concludes with a summary of the complete system as delivered to PHSI and FC inspectors for field testing and feedback.

6.1   Requirements and Overview

The primary objective of the project, as defined by DEFRA is as follows:

"To develop a real-time hand-held device (or alternative platform compatible with PH-SI/FC equipment) capable of detection and identification of a range of taxa in hard plant materials (including standing trees) for PHSI inspectors, and potentially FC inspectors, to evaluate. To develop a real-time species detection and identification data logging system for deployment and monitoring over an extended period of time. To develop a live insect (non-specific) detection system."

Any acoustic detection system, whether automated or manual, requires at least the four stages shown in figure 6.1.
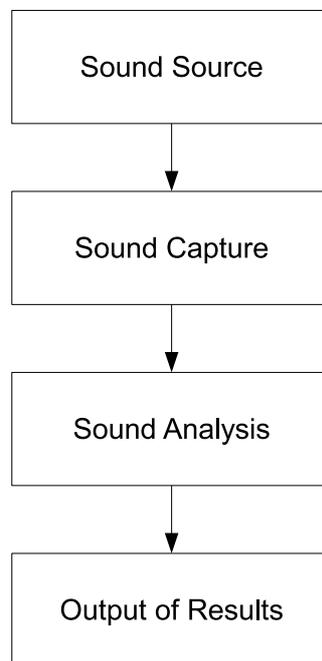
Figure 6.1: Components of a Detection System

The sound source is considered to be the combination of tree or wood sample with unknown quantity and species of larvae inside; this has been discussed in chapter 3. DEFRA require two systems, a hand-held device and a data-logging device, both of which will perform automated insect detection and identification. The specified and implied requirements for these devices are set out in tables 6.1 and 6.2.

Requirement	Explicit	Implicit
Real-time Detection	•	
Real-time Identification	•	
Non-destructive Attachement	•	
Robust (for outdoor use)		•
Real-time output	•	
Compatible with PHSI/FC equipment	•	
Simple to operate, requiring no specialist knowledge of underlying methods		•
Battery life suitable for field use		•
Produce reliable results		•
Sensors easily attachable and detachable		•
Expandable		•

Table 6.1: Hand-held System Requirements

Requirement	Explicit	Implicit
Automated Detection	•	
Automated Identification	•	
Non-destructive Attachment	•	
Weatherproof; suitable for prolonged periods of outdoor use		•
Output to storage	•	
Compatible with PHSI/FC equipment	•	
Simple to operate, requiring no specialist knowledge of underlying methods and minimum user interaction		•
Battery life suitable for extended periods of field use		•
Produce reliable results		•
Sensors easily attachable and detachable		•
Expandable		•

Table 6.2: Data-logging System Requirements

The two systems share many of the same requirements; the only significant differences between the two are in battery life requirements, user interface and whether real-time

analysis is required or not.

The data-logging system does not need to perform data analysis in real-time. In principle it could be based around a simple audio recorder which could store data to a removable disk which could then be uploaded to a PC or other dedicated device for analysis. This option was considered but was concluded to have several limitations; large amounts of storage space are required since all recorded audio has to be stored for analysis. Perhaps more significantly, the system would be unable to give any indication of the potential presence of any infestation whilst in place since results would only be available to the user after data was uploaded for analysis.

A decision was taken to focus on producing a single system which could be used as both data-logger and hand-held device. No indication was provided by DEFRA or PHSI as to the battery life requirements of either system nor how it was envisaged that such a device were to be used. The limited information known about larval feeding behaviour when inside wood also presented difficulties in specifying some aspects of the design. For example, the presence of larvae does not imply the presence of detectable acoustic activity since larvae don't feed continuously. Therefore the longer a sample is monitored for, the greater the chance of detecting any infestation which is present.

6.2   Recording Equipment and Methods

In the early stages of this project a number of recordings were made using simple piezo-electric sensors in combination with hard disk and solid state disk based audio recording devices. The purpose of this was two-fold; firstly it was used to test various aspects of the sensor design and secondly it was used to build up a larger library of recordings. The majority of these recordings were made within quarantine facilities with a limited number being field recordings.

The recording devices used were the Edirol R4, Edirol R-09HR and the Marantz PMD660. The Edirol R4 is a four channel hard disk based recorder which supports sampling rates up to 96kHz with 16 or 24 bits per sample. The 40GB hard disk provides enough storage space for 29 hours worth of recording when using four channels at 44.1kHz with 16 bits per sample. It can be powered by either mains or batteries but both of these

options have limitations. Firstly, the batteries tended to run out very quickly, often lasting little over an hour; secondly the mains power introduced a huge amount of mains noise into the recordings. The R09HR and PMD660 are portable two channel devices which record to secure digital (SD) and compact flash memory card respectively.

The sensors used were Kingstate KPEG116 piezoelectric transducers which were placed inside plastic housings packed with foam and sealed closed. The piezoelectric transducers were held in place only by the pressure of the layers of foam padding; no glue was used. Figure 6.2 shows the side view of the sensor construction.
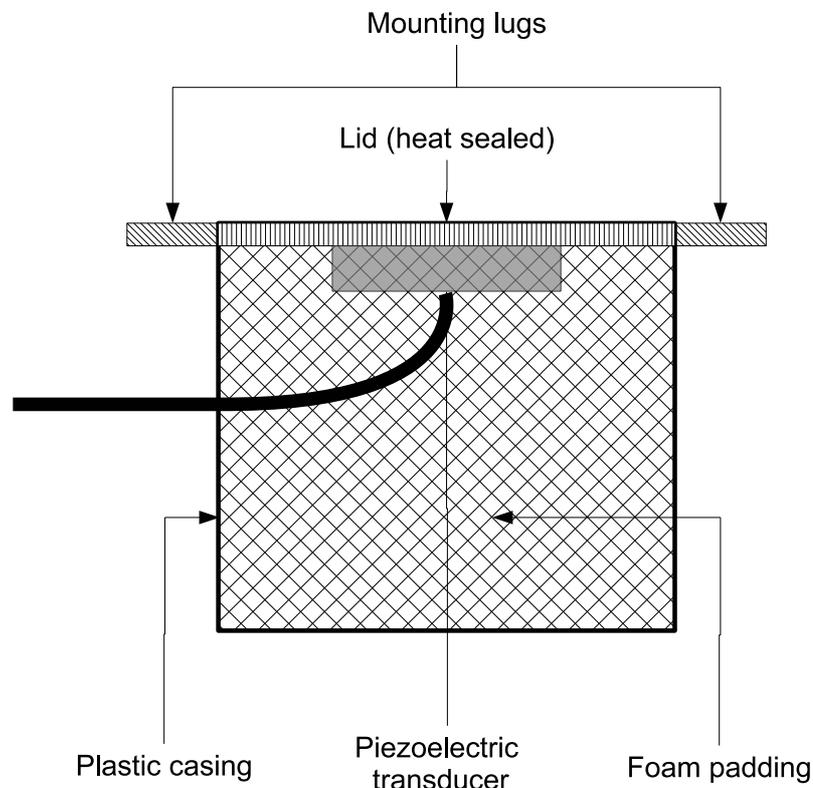
Figure 6.2: Side view of encased sensor

The method of attaching the sensor was dependent on the size of the sample. Rubber bands were used on small tree trunks and pieces of timber while rubber tree straps were used for larger standing trees. Sensors in place attached to samples using both methods can be seen in Figures 6.3 and 6.4.

Figure 6.3: Sensor attached using a tree strap

A number of 'speculative' recording sessions were undertaken throughout the course
of the project. These involved making recordings of samples which came from potentially
infested shipments of material or trees but where the infestation status of the individual
samples was unknown. These proved to be of little use to the project since the detection of
activity was very rare; this could be attributed to the lack of infestation or activity, or due
to poor performance of the detection system. The manual processing of the resultant audio
data was required and more often than not the cause was lack of larval activity. Towards
the end of the project, FERA obtained a number of live *Anoplophora glabripennis* larvae
which were placed inside inside tree stumps to allow the system to be tested with known
infested material. A full list of the recordings made during this project is provided in
Appendix D.

6.3   Hardware Implementation

6.3.1   Sound Cards and USB Sensors

It is very uncommon for a PC, hand-held or otherwise, to have no inbuilt sound card. A
sound card is a device which provides a PC with the capability to output and/or input au-

Figure 6.4: Sensor attached using rubber bands

dio, usually both. Most sound cards provide at least analogue microphone input, analogue line level input and analogue loudspeaker output with many also featuring digital input and output (SPDIF - optical, composite or both) and various other analog outputs for surround-sound systems. These devices tend to follow, sometimes loosely, Intel's Audio Codec 97 specifications, now at revision 2.3 (Intel, 2002). Table 65 of the specification document lists various analogue performance characteristics, those relevant to this project are reproduced here in table 6.3.

Parameter	Minimum	Typical	Maximum	Units
Full Scale Input (Microphone)	-	0.1	-	Vrms
Full Scale Input (Line Level)	-	1.0	-	Vrms
Analogue Frequency Response	20	-	20,000	Hz
Input Impedance	10	-	-	$k\Omega$
Input Capacitance	-	7.5	-	pF
Input Channel Crosstalk	-	-	-70	dB

Table 6.3: Selection of AC '97 Analogue performance characteristics

It was initially envisaged that the sensors would be directly connected to the analogue microphone input of whichever integrated sound card was fitted. Early testing uncovered several potential issues with this approach for which various solutions were considered; these are summarised below.

1. When the PC was accessing the hard disk significant levels of noise were introduced to the input channels of the sound device. An external sound device or analogue to digital converter could be used to eliminate this type of noise.

2. There are variations between sound cards in different PCs which could affect the recordings made with them. Whilst this would not be an issue if a single type of hand-held PC was being used, during development the sensors were used with various machines and for convenience the elimination of any variation was preferable.

3. The use of an integrated sound card would limit the system to using a maximum of two sensors at any one time. If one of the channels is used for an ambient sound sensor then only one sample sensor could be used. 'Time slicing' could be used to connect multiple sensors per channel, alternatively USB connection could be used which would increase the potential number of concurrently attached sensors.

4. The requirement of an analogue audio input limits the potential choice of hand-held PC's since several do not have this type of connection, instead having integrated microphones which are not suitable for use in the recording of larvae.

5. There is a risk of user error associated with using analogue audio input since identical jacks are used for line-level input, headphone output and various surround-sound outputs.

6. The sensors will require a pre-amplifier. The power source for this will either need to be a battery built into the sensor, microphone phantom power from the sound card or from a USB port.

7. Various configuration options relating to the default sound card on a Windows machine tend to change without warning. Gain levels in particular seem to be particularly susceptible to this.

The combination of these issue led to the development of a new sensor which combines a USB audio circuit with in-built amplification. These units make use of the two audio channels available by the addition of a secondary sensor which is used to detect acoustic events which are not produced by larvae, to reduce the rate of false positive detections. An overview of the sensor design can be seen in Figure 6.5.
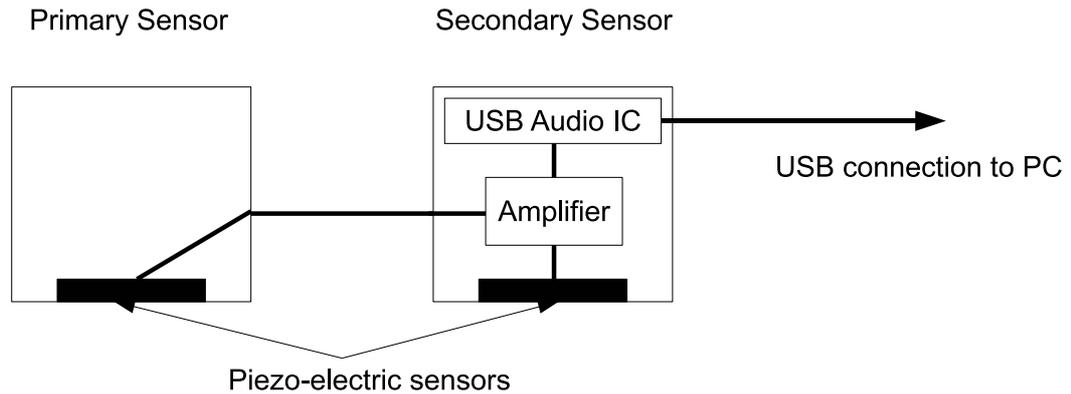
Figure 6.5: USB Dual Sensor Design

These sensors provide recordings which are independent of the PC hardware to which the sensor is connected. An additional benefit is that the bite detection software is able to monitor for the presence of attached sensors and produce warnings when they are removed.

6.3.2 Hand-held PCs and embedded devices

The hand-held PC is a standard 'off the shelf' product, the Samsung Q1. This was selected as a prototype based upon its comparatively long battery life and availability of low cost ruggedised cases which are essential for its use in a field environment.

PC hardware improves rapidly over time and it is very likely that a more suitable device is now available. Any future version of the system would ideally have better specified requirements by FERA which may result in a significantly different hand-held device being used.

6.4 Software Implementation

This section is intended to serve as an overview of the software's capabilities and basic structure rather than a full implementation report. The detection software is capable of fully automated real-time analysis when capturing sound directly from an attached sensor. It can also perform non-real-time or simulated real-time analysis of imported recordings stored as audio files. It is written in Microsoft C♯ and requires the .NET Framework 2.0 and Direct X Direct Sound library and is therefore dependent on the windows platform; an overview of the software is provided in Figure 6.6.
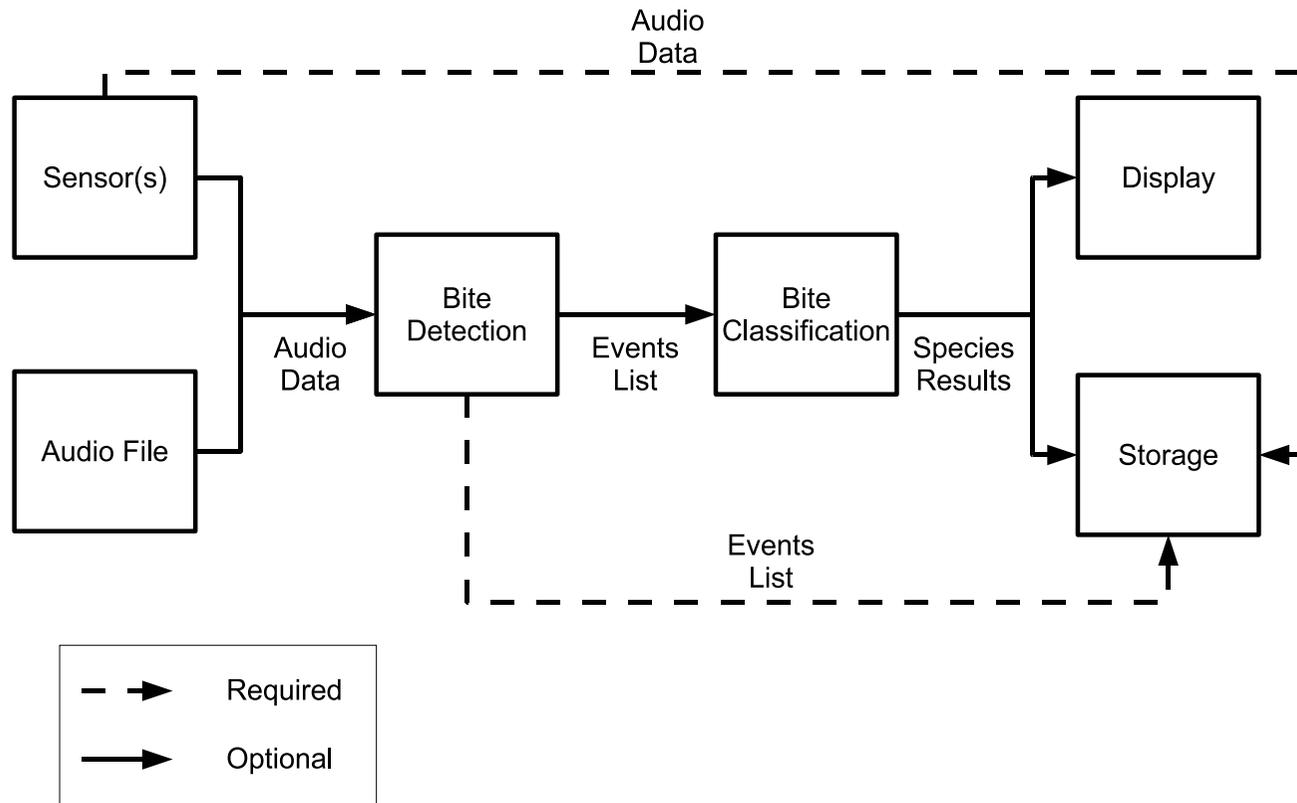
Figure 6.6: Software Overview

6.4.1 Inputs

The first stage in the software is the selection of an audio source which will be analysed. At the request of FERA, the software allows multiple types of input audio source to be used in addition to the recommended USB sensors.

1. **Mono Audio File** A prerecorded audio file can be opened for analysis. This can optionally be run through the system in 'real-time' to simulate the presence of an attached sensor. Any saved events such as bite audio files or species results are time-stamped with their position within the original file.

2. **Stereo Audio File** As for mono audio files except that a second channel is provided as the ambient sound, or control, source. The channel providing containing ambient sound can be selected so that the system can cope with recordings which have been made with the sensor channels swapped.

3. **USB Sensor** This tells the software to record audio from an attached USB sensor and is the suggested method of using the system. If no sensor is attached to the PC this option is not enabled. The USB sensors record two channels, one for the subject, one for ambient sound. The channels used for these sensors are fixed since the user cannot physically switch them around.

4. **Sound card input** The option to allow the use of a built in PC sound card was added at the request of FERA. As has been discussed earlier in this chapter, internal PC sound cards are not well suited for use in a system such as this and this input method is therefore not recommended.

The expected input format is uncompressed pcm audio data sampled at 44.1kHz with 16 bits per sample. If a USB sensor or internal sound input is being used the software will attempt to initialise the audio device with these parameters which are supported by the vast majority of PC sound devices. If the input source being used is an audio file the software will expect a file in WAVE format with the above parameters. Sampling rates other than 44.1kHz are supported but the fractal analysis frame size must be adjusted accordingly since it is measured in samples rather than seconds.

6.4.2 Detection

In this section the event detection aspect of the software will be discussed. This task can be considered independently of the other functions of the software since the analysis is performed linearly on fixed input data to produce a single set of outputs. The input to the detection stage is a segment of mono audio data, if a single sensor is being used, or stereo data if an ambient sensor is also attached.
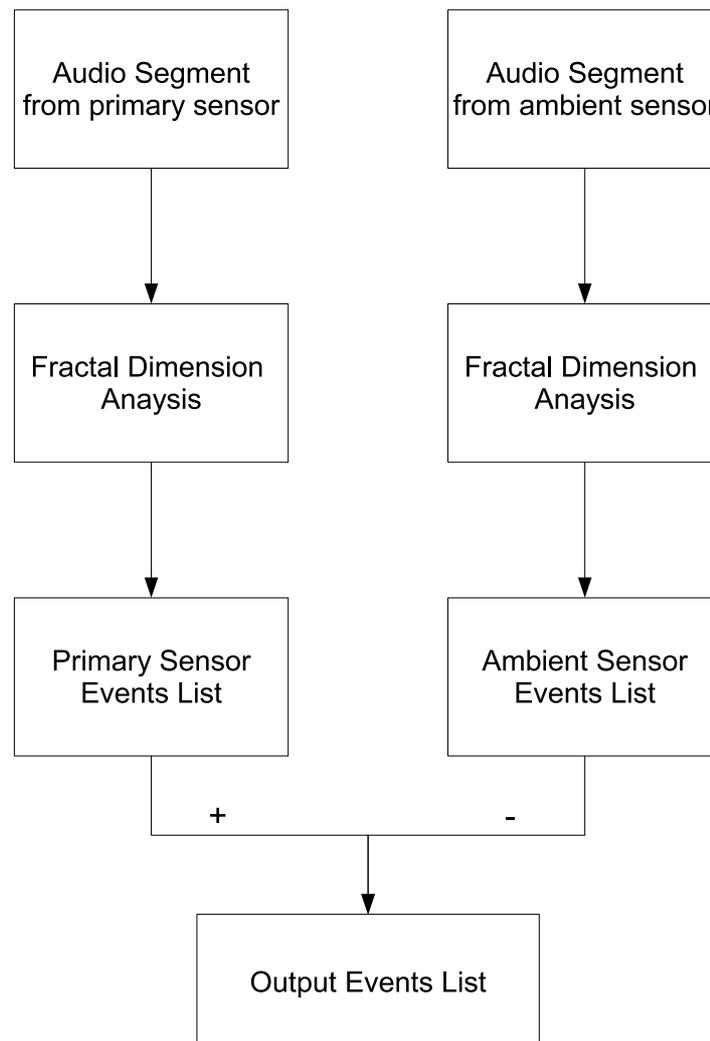
Figure 6.7: Detection Process

Incoming audio data from either sensors or a WAVE file is provided to the bite detector in segments which are one second in length. This length is used to allow the system to provide a near-realtime indication of any detection whilst also being of sufficient length to enable the average based thresholding used by the detection method to operate.

For each segment, the fractal dimension detection method described in chapter 4 is used to generate a list of frames and their respective detection results (either ones or zeros). Given a frame size of 300 samples, the example frame list results shown in table 6.4 correspond to a single event positioned at between 1500 and 2100 samples in the audio segment.

Frame Position	Detection (0 = No, 1= Yes)
0	0
1	0
2	0
3	0
4	0
5	1
6	1
7	1
8	0
9	0
10	0

Table 6.4: Example Frame Results Table

If two sensors are present the detection results for all fractal dimension frames within the audio segments are compared. Any frames which have been registered as containing an event from the ambient channel are set to zero in the primary channel. This means the output event list only contains events which have been registered exclusively in the primary sensor channel. Table 6.5 is a truth table for this operation.

Primary Sensor Event List	Ambient Sensor Event List	Output Event List
0	0	0
0	1	0
1	1	0
1	0	1

Table 6.5: Events List Truth Table

A list of events including start and end positions, in samples, is produced. Events which are located very closely together are merged and events which exceed a predefined maximum event length are excluded. The list of detected events is then passed to the classification stage and optionally stored as individual audio files.

6.4.3 Identification

The identification stage takes as its inputs the list of detected events as produced by the detection stage, and the original audio segment data. The classification process is visualised in Figure 6.8.
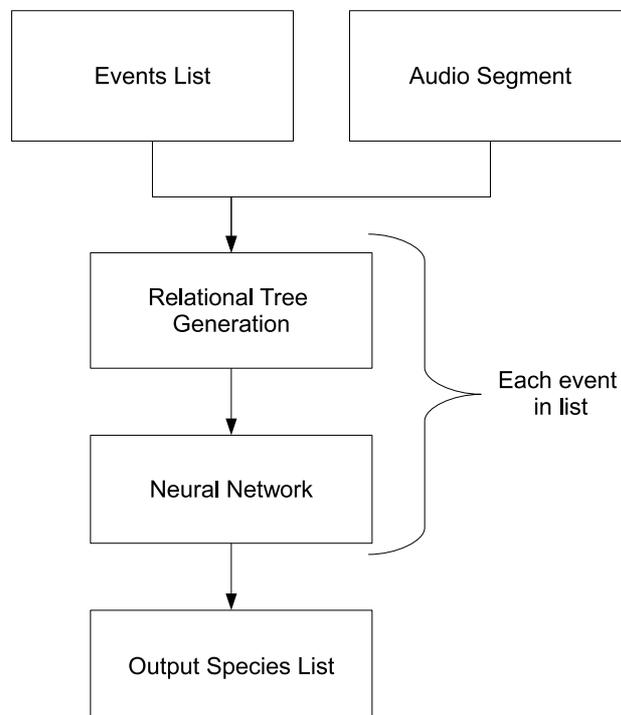
Figure 6.8: Bite Identification Process

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The relational tree generation feature extraction method and LVQ neural network described in Chapter 5 are used to classify bite species. Once all detected events have been classified the results are displayed on screen and optionally written to the hard disk.

The version of the software which was supplied to DEFRA did not have the bite identification stage enabled.

6.4.4   Threading

The software makes use of three threads which allow it to perform real-time analysis whilst simultaneously recording new data and keeping the user interface updated with results. The primary duties of, and communication between these threads can be seen in Figure 6.9.
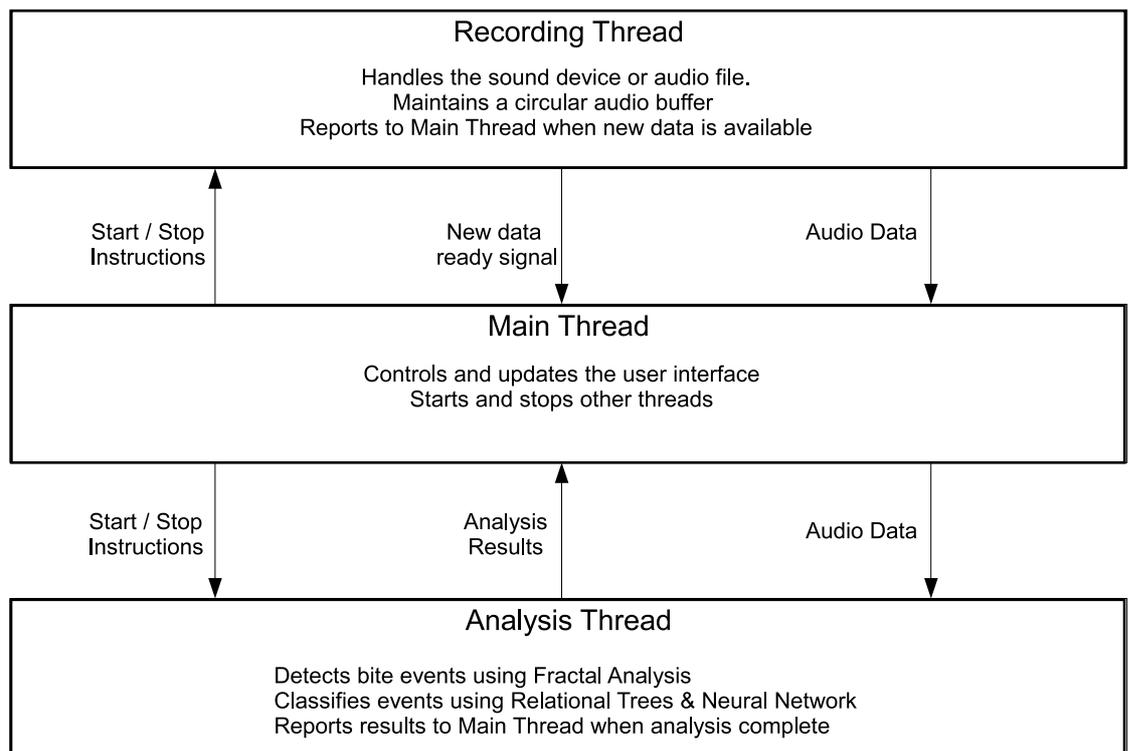
Figure 6.9: Threads

When the software is first started only a single thread, the main thread, is active. This controls and updates the user interface and starts other threads in response to user input. When the user instructs the software to start recording, the recording thread is

started; subject to the successful initialising of the requested sound device. The recording thread then runs continuously alongside the main thread capturing audio from the sound device and reporting back when new audio data is available for analysis until it receives an instruction to stop. The main thread starts a new instance of the analysis thread each time new audio data is available. This then analyses the segment of audio data before returning results to the main thread before terminating itself.

6.4.5 System Output and Data Storage

Data collected at each of the stages shown in Figure 6.1, recording, detection and identification, can be stored for later use. At the recording stage this is in the form of a single WAVE audio file containing unmodified data as captured by the USB sensor(s). At the detection stage, events which exceed the required threshold are stored individually as WAVE audio files with time stamps indicating when they were detected. At the identification stage the species, if any, of detected events can be stored along side a time stamp for the event.

6.4.6 Limitations

The software is limited to supporting a maximum of two attached sensors; one for attaching to samples and the other to capture ambient sound. The underlying code is capable of supporting a greater number of sensors and this support could be enabled if needed by PHSI subject to suitable testing being carried out to determine the upper limit attached sensors.

The maximum file size which can be loaded for analysis is 512MB as larger files produce 'out of memory' errors. This can be overcome by the use of a more efficient file loading routine.

6.5 Complete System

The complete system delivered to PHSI for testing consisted of the following:

Hand-held PC

- Samsung Q1 Ultra Portable PC

- 40GB hard-disk storage (capable of storing over 3,000,000 bites)

- Operating System: Microsoft Windows XP Tablet Edition

- 4AH battery (providing around 8 hours continuous usage)

- Cost per unit   £400

- Acoustic bite detection software installed

Acoustic Sensors

- Dual sensor system

- Piezo-electric transducer sensors in plastic ABS casings

- USB Audio using Texas Instruments PCM2902 chips

- Audio pre-amplifiers providing a gain of 20

Peli-Case

- Large shock-proof case containing the above items in addition to:

- Stereo headphones

- Rubber tree straps for attaching sensors

- Power adaptor for hand-held PC

6.6   Summary

In this chapter the requirements for the hand-held and data-logging systems as defined by DEFRA were considered. The generalised requirements for an acoustic detection system were discussed in addition to the specific requirements of the two automated systems. The recording methods used before the development of the automated system were discussed along with the initial designs of the sensors used in these recording sessions.

The hardware implementation of the system including the use of USB attached sensors with built in pre-amplification was then detailed in section 6.3. Section 6.4 provided an overview of the software implementation including methods of input, analysis and output to storage and display. Finally the complete system as supplied to PHSI for testing was described in section 6.5.

Figure 6.10: Complete System

Chapter 7

Conclusions and Further Work

7.1 Conclusions

Invasive Non-Native Species are a constant threat to the U.K. environment and economy. A group of species which are of particular concern to DEFRA at present are wood-boring beetles. These insects spend a high proportion of their life-cycles as larvae inside timber and trees and are therefore difficult to detect.

Current detection techniques employed by PHSI inspectors rely on visual inspection such as looking for beetle exit holes or frass; and manual destructive sampling. Visual inspection may not provide a reliable indication of infestation, particularly if no adults have emerged from a sample; destructive sampling is a time consuming process and may not be financially viable for consignments of high value plants. DEFRA are therefore interested in the development of techniques to detect larvae in a non-destructive manner.

The stated purpose of this project is "to aid the work of the Plant Health and Seeds Inspectors (PHSI) and Forestry Commission (FC) inspectors by improving their ablity to detect a range of statutory/quarantine pests using the acoustic methods initially investigated in a previous Plant Health Division funded project PH0191, which established proof of principle" (DEFRA, 2007).

The piezo-electric sensors used in the previous project (PH0191) were tested and their performance relative to new low cost accelerometer based sensors was investigated. It was concluded that the accelerometer based sensors provide no significant advantage over the

piezo-electric sensors and are more expensive to produce, more complex and more difficult to acoustically couple with sample material; their suitability was therefore discounted.

A low cost (both computationally and economically) dual sensor method has been suggested in order to further reduce the rate of false positive detections. These incorporate USB audio and amplification circuitry which enable recordings to be made with consistent characteristics and gain which is independent of the PC hardware to which they are connected. The use of a new technique for bite event detection, Fractal Dimension (FD) detection, has been introduced in Chapter 4 and it has been shown to perform significantly better than short time energy detection for events with low signal to noise ratios. At a signal to noise ratio of 2, the difference from the mean value in fractal dimension for bites is 6.61, compared to an equivalent short time energy difference of 2.03. This advantage enables fractal dimension detection to be used to detect bites at lower signal to noise ratios.

Limitations in the use of TDSC as a feature extraction method for bite waveforms have been demonstrated and a novel method for the extraction of features from bite sounds based upon relational tree structures has been developed. The performance of this method in combination with Multilayer Perceptron and Linear Vector Quantisation neural networks has been assessed in Chapter 5.

Classification between two species, *A. glabripennis* and *H. bajulus* has been achieved with rates of 92% using MLP and 96.5% using LVQ networks. Classification between the two species and noise has been achieved with rates of 88.7% using MLP and 95.6% using LVQ. Classification between three species *A. glabripennis*, *A. planipennis* and *H. bajulus* has been achieved with a rate of 88.8% using an LVQ network.

The detection and identification methods developed here have been implemented in a prototype real-time hand-held PC based system which has been supplied to FERA for further testing.

7.2 Evaluation of the adopted system

The system can provide a real-time indication of potential larval activity, however if all larvae in the sample are not feeding the system will provide a false negative result. With-

out extensive behavioural study of larvae it is impossible to quantify the confidence in any real-time detection result since the percentage of time a larva spends feeding is unknown. The longer the system can be attached to each sample, the greater the likelihood of detecting any larval infestation. Until data on the feeding behaviour of larvae is obtained, the time required to accurately analyse each sample cannot be calculated. The use of the detection and identification methods developed may best suited to long term monitoring of host plants.

The number of species which the system can identify is currently very low; the species classification aspect of system in it's current state has limited practical usefulness. In order to scale up the system to perform identification of a wider range of species the classification method used may require significant alteration. The classification rates achieved for three species detection were lower than those for two species. It is likely that if the neural network was trained with additional species, the classification rate would decrease further. If larger data sets could be obtained for each of the species it is possible that classification rates may be attained by changing the topology of the neural networks by, for example, increasing the number of neurons.

It is very unlikely that the system could be scaled up indefinately to cope with the identification of all possible species of beetle without the use of prior knowledge such as tree species or location within the tree. It is however, unlikely that a situation would arise in which the system would be required to classify a large number of species.

The hardware and software system produced and supplied to FERA can be considered to be a prototype rather than a final system. Very little information was provided regarding specification requirements such as battery life, species range and deployment environment. Several software and hardware design decisions reflect the lack of specification from FERA and were taken to make the system as flexible as possible. The software was written in C♯ to allow it to run on most modern desktop and laptop PCs whilst also being simple to port to Windows based embedded PCs, handhelds or even mobile phones. The PC hardware, the Samsung Q1, was selected primarily for it's long battery life of up to 10 hours. Sensors were produced with embedded sound cards and USB connectivity to ensure that they would be compatible with other PC hardware.

If the system requirements were strictly specified by FERA and sufficient supplies of larvae were available for the generation of a large library of feeding sounds, both the hardware and software used in the system would likely change significantly from the current design.

7.3 Further Work

7.3.1 Beetle Species Range

The results presented in this thesis have been limited to a small number of beetle species due to the difficulty in obtaining known infested material, particularly where the desired species is an INNS. In order for the species identification aspect of the system to be of real practical use, the range of species which can be classified needs to be expanded. It is not currently known how well the classification methods would perform with a large range of species.

The methods here could be combined with additional information which could assist classification such as the sample species, geographic information or time of year. Information such as this could be used to produce a knowledge based system which would be able to partition the classification space based upon prior knowledge of the likelihood of certain species being present.

7.3.2 More Recordings

This research has been limited by the availability of known infested material which can be recorded; access to quarantine species for recording is for obvious reasons rather difficult. The methods and system developed could be improved based upon information obtained from a much larger set of recordings. This would also enable the classification techniques to be further validated.

A large set of recordings made in varied environments may also provide useful information relating to the biological study of the species such as host preferences.

7.3.3   Behavioural Study

There is still relatively little known about the feeding behaviour of beetle larvae in wood. The detection methods developed here could be used to produce and analyse recordings of a wider range of species over long time-periods. This would enable a greater understanding of how feeding is effected by various external and internal factors. For example, anecdotal evidence was obtained during the course of this research that larvae may be sensitive to the sudden movement of their host material (See Chapter 4) and that the rate of feeding activity may be related to the time of day.

Behavioural information could then be used to improve the performance of a detection system either by utilising this knowledge within the system itself or by adjusting the way that it is used in order to maximise the likelihood of detection.

7.3.4   Wireless Sensor Networks

The techniques developed here could be extended to a large scale network of sensors, used to monitor greater numbers of trees over long time periods. Such a network may be of particular use in conjunction with sentinel trees when used to monitor the spread of infestations or to monitor consignments of imported trees during post import growth.

It has been shown in Section 5.2.5 that the relational tree feature extraction method represents bite audio data in a significantly compressed format. This could be exploited in a wireless sensor network since feature data could be transmitted to a central classification system using low bandwidth data links.

7.3.5   Native Species

The research undertaken so far has concentrated on the detection and identification of non-native species. The methods here could be used to detect native wood-boring species and may be suited to applications in the area of preservation of wood in listed buildings. Piezo-electric sensors similar to those used in this research are currently being used in the non-invasive monitoring of stag beetles (*Lucanus cervus*) (Harvey et al., 2011).

Appendix A

Publication List

Schofield, J. & Chesmore, D. (2008) *Automated acoustic identification of beetle larvae in imported goods using time domain analysis.* Proceedings of Acoustics 2008, Paris, June 2008, 5929-5934.

Chesmore, D. & Schofield, J. (2009) *Developing acoustic detection and identification methods for Anoplophora spp. Second International Symposium on Anoplophora chinensis and A, glabripennis: Phytosanitory Strategies and Research,* Vertemate Con Moniprio, Como, Italy, 1-3 April 2009.

Schofield, J . & Chesmore D. (2010) *Automated identification of beetles in hardwood.* Royal Entomological Society Technological Special Interest Group, Harpenden, 13 May 2010.

Schofield, J. & Chesmore D. (2010) *Acoustic detection and monitoring of wood boring beetles.* Entomology 2010, Swansea, 26-28 July 2010.

Chesmore, D. & Schofield, J. (2010) *Acoustic detection of statutory pests in hardwood material.* Bulletin of the European Plant Pathology Organisation (EPPO).Vol. 40(1), 46-51.

Appendix B

Fractal Dimension C# Code

```csharp
static double[] sevcik_fractal(short[] data, int frame_length)
    {
        double ymax = 0, ymin = 0, length, d, y_current, y_old;
        int start_frame_pos, end_frame_pos;

        double[] d_array = new double[data.Length/frame_length];

        for (int frame=0; frame<(data.Length/frame_length); frame++)
        {
            length = 0;
            y_current = 0;
            y_old = 0;

            start_frame_pos = (frame * frame_length);
            end_frame_pos = (frame * frame_length) + frame_length;
            ymin = ymax = data[start_frame_pos];

            for (int i = start_frame_pos+1; i<end_frame_pos; i++)
            {
                    if (data[i] < ymin) ymin = data[i];
                    if (data[i] > ymax) ymax = data[i];
            }
```

```
            y_old = (data[start_frame_pos] − ymin) / (ymax − ymin);


        for (int i = start_frame_pos+1; i<end_frame_pos; i++)
        {
                y_current = (data[i] − ymin) / (ymax − ymin);
                length += Math.Abs(y_current − y_old);
                y_old = y_current;
        }


        d = 1 + Math.Log(length) / Math.Log(2 * (frame_length − 1));
        d_array[frame] = d;
    }
    return d_array;
  }
}
```

Appendix C

Additional Classification Results

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	90	10
H. bajulus	6	94
Confidence	0.938	0.904

Table C.1: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 200 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	90	10
H. bajulus	6	94
Confidence	0.938	0.904

Table C.2: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 100 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	89	11
H. bajulus	6	94
Confidence	0.937	0.895

Table C.3: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 50 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	89	11
H. bajulus	6	94
Confidence	0.937	0.895

Table C.4: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 20 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	91	9
H. bajulus	7	93
Confidence	0.929	0.921

Table C.5: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 10 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	92	8
H. bajulus	10	90
Confidence	0.902	0.918

Table C.6: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 4 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	92	8
H. bajulus	10	90
Confidence	0.902	0.918

Table C.7: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 2 levels

Classified as →	A. glabripennis	H. bajulus
A. glabripennis	94	6
H. bajulus	20	80
Confidence	0.825	0.930

Table C.8: *A. glabripennis* vs. *H. bajulus* MLP, Depth 4, Quantization 1 level

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	88	10	1
H. bajulus	8	89	4
Noise	4	4	91
Confidence	0.880	0.864	0.948

Table C.9: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 200 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	90	9	1
H. bajulus	7	90	4
Noise	4	5	90
Confidence	0.891	0.865	0.947

Table C.10: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 100 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	89	10	1
H. bajulus	8	89	4
Noise	4	4	91
Confidence	0.881	0.864	0.948

Table C.11: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 50 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	90	9	1
H. bajulus	10	87	4
Noise	4	4	91
Confidence	0.865	0.870	0.948

Table C.12: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 20 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	88	10	2
H. bajulus	8	87	6
Noise	4	4	91
Confidence	0.880	0.847	0.919

Table C.13: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 10 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	88	9	3
H. bajulus	3	93	5
Noise	2	3	94
Confidence	0.946	0.809	0.922

Table C.14: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 4 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	83	13	4
H. bajulus	10	84	7
Noise	3	5	91
Confidence	0.865	0.824	0.892

Table C.15: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 2 levels

Classified as →	A. glabripennis	H. bajulus	Noise
A. glabripennis	65	33	2
H. bajulus	12	83	6
Noise	4	4	91
Confidence	0.802	0.692	0.919

Table C.16: *A. glabripennis* vs. *H. bajulus* vs. Noise MLP, Depth 4, Quantization 1 level

Appendix D

Recordings made during this project

Date	Location	Samples	Duration
20.02.09	CSL Quarantine Lab	1x Headboard pest	30 Mins
13.03.09	CSL Quarantine Lab	1x Headboard pest	24 Hours
06.04.09	Assago, Milan, Italy	3 trees infested with A. chinensis	2 Hours
01.06.09	CSL Quarantine Lab	1x mini-Acer	24 Hours
18.06.09	CSL Quarantine Lab	3x mini-Acer, 1 x wooden bowl	24 Hours
23.03.10	CSL Quarantine Lab	Wooden post infested with *Monochamus galloprovincialis*	24 Hours
02.06.10	National Reference Laboratory, Netherlands	Acers inoculated with *A. chinensis*	2 Hours
24.06.10	Kew Gardens	Various	1 Hour
25.06.10	CSL Quarantine Lab	4x Acers and Poplars with *A. glabripennis*	24 Hours
14.07.10	CSL Quarantine Lab	4x Acers and Poplars with *A. glabripennis*	24 Hours
07.10.10	CSL Quarantine Lab	4x Acers and Poplars with *A. glabripennis*	24 Hours
12.10.10	CSL Quarantine Lab	4x Acers and Poplars with *A. glabripennis*	24 Hours
20.10.10	CSL Quarantine Lab	4x Acers and Poplars with *A. glabripennis*	24 Hours

Table D.1: List of recordings made during this project

Appendix E

Recordings made by others

Source	Location	Species	Details
Previous Project PH0109 [Farr, 2007]	CSL Quarantine Lab, York	*H. bajulus*	File: 2005 06 30 CSL 30 June 2005 Hylotrupes Bajulus Block 005A 002.wav
FERA	FERA Quarantine Lab, York	*A. glabripennis*	Recordings made during March 2011
Universita Degli Studi Die Padova, Italy	Italy	*A. glabripennis*	Recordings made early 2011
Canadian Food Inspection Agency	Outdoor Quarantine facility, Canada	*A. planipennis*	

Table E.1: List of recordings made by others

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