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Improving the Efficiency and Accuracy of Nocturnal Bird Surveys through Equipment Selection and Partial Automation

Ljubica Lazarevic

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Volume I of II

Reader's Guide

This EngD portfolio consists of two volumes. Volume I is a thesis that covers the main research activities and contributions to knowledge of the EngD. The EngD programme also requires the submission of progress reports every six months throughout the four years. These six-monthly progress reports make up Volume II of the portfolio. Due to the nature of the portfolio, much of the content of the progress reports is repeated in the thesis. **It is only necessary to read the thesis (Volume I) to understand the core research project and the contributions to knowledge that have been made.** Volume II gives an idea of the progress throughout the four years and how the project developed.

Declaration of Authorship

I, Ljubica Lazarevic, declare that this thesis titled "Improving the Efficiency and Accuracy of Visual-Based Nocturnal Bird Surveys through Equipment Selection and Partial Automation" and the work presented in it is my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated
- Where I have consulted the published work of others, this is always clearly attributed
- Where I have quoted from the work of others, the source is always given
- With the exception of such quotations, this thesis is entirely my own work
- I have acknowledged all the main sources of help
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Abstract

Birds are a key environmental asset and this is recognised through comprehensive legislation and policy ensuring their protection and conservation. Many species are active at night and surveys are required to understand the implications of proposed developments such as towers and reduce possible conflicts with these structures. Night vision devices are commonly used in nocturnal surveys, either to scope an area for bird numbers and activity, or in remotely sensing an area to determine potential risk. This thesis explores some practical and theoretical approaches that can improve the accuracy, confidence and efficiency of nocturnal bird surveillance.

As image intensifiers and thermal imagers have operational differences, each device has associated strengths and limitations. Empirical work established that image intensifiers are best used for species identification of birds against the ground or vegetation. Thermal imagers perform best in detection tasks and monitoring bird airspace usage.

The typically used approach of viewing bird survey video from remote sensing in its entirety is a slow, inaccurate and inefficient approach. Accuracy can be significantly improved by viewing the survey video at half the playback speed. Motion detection efficiency and accuracy can be greatly improved through the use of adaptive background subtraction and cumulative image differencing.

An experienced ornithologist uses bird flight style and wing oscillations to identify bird species. Changes in wing oscillations can be represented in a single inter-frame similarity matrix through area-based differencing. Bird species classification can then be automated using singular value decomposition to reduce the matrices to one-dimensional vectors for training a feed-forward neural network.

Key Words: Nocturnal Bird Surveys, Surveillance, Infrared, Bird Classification, Cyclic Motion Detection, Similarity Matrix, Singular Value Decomposition, Time Lapse, Motion Detection

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Glossary

Below are a number of terms that have not been explicitly defined within the thesis that the reader may find useful.

Artefact Aliasing – when a 'twin' object appears due to frame capture problems.

Barrier Effect – a term used to describe an impact a structure may have on fauna. Barrier effect implies that a structure causes the area it is situated in to deter fauna from approaching, even if the structure does not necessarily confine the whole area it occupies. An example is a wind farm.

Eye Shine – light reflected from an animal's eye. Typically found with nocturnally active fauna.

Field of view – in degrees, the amount of area a camera can capture from a stationary point with its lens.

Fourier Transform – a transform that essentially converts the input data to frequency domain. The frequency domain shows signal quantity per frequency band, rather than the time domain that shows signal change per time band.

Frame Grabber – a device that is used to convert analogue video into digital video.

Frame Rate – the number of images or frames captured or viewed per second

Gaussian Distribution – Same as normal distribution

Remote Survey – recording equipment, such as a thermal imager with video output stored digitally to a computer is installed in a location where it will be left for a duration of time.

Scoping Survey – a form of survey where an initial idea as to what fauna may be using the area is sought. Some numbers and activity information may be gathered, but information such as flight heights, flight lines, or area usage may not necessarily be collected. These surveys are carried out by surveyors that are continuously monitoring the site.

Vantage Point Survey – a surveyor observes a certain viewshed from a fixed location.

Viewshed – the total area a surveyor can observe whilst panning a visual device. Different from field of view.

Waterbird – collective term to describe ducks, geese, swans and waders.

Wildfowl – collective term to describe ducks, geese and swans.

Wing Beat Frequency – The rate at which wings beat. This is usually beats per second. A typical measure used in radar observation of birds.

Executive Summary

Background

With the potential for adverse environmental impacts, man-made structures must undergo rigorous planning and assessment prior to construction. To assist with the assessment of development risk of large structures to birds, diurnal surveillance is used to gain primary information of birds present in the area with nocturnal surveillance being used but rarely. Given that equipment for these surveys is becoming more widely available, this is not acceptable and nocturnal surveillance need to be developed and undertaken as standard.

Thermal imaging and image intensifying equipment provide a convenient way to survey birds at night. Many forms of these night vision apparatus are portable, easy to use and the surveyor obtains instant feedback as to what can currently be viewed. The survey area can be quickly scanned for bird activity and over an evening's surveillance, information on bird numbers, distribution, species and activity can be obtained. Fixed point surveillance can be used to understand the usage of airspace by birds. This is important when trying to understand the potential risk of birds flying at turbine blade height. Recording video from the imaging device for the entirety of an evening from fixed point surveillance is the most practical approach; fewer surveyors are required and the video data can be analysed in more convenient circumstances.

There is a lack of consensus as to when and where to use thermal imagers or image intensifiers. Very little past work from previous sources has examined both types of night vision devices under comparable scenarios, especially when surveying for birds. As thermal imagers and image intensifiers are operationally different it is important to be aware of the strengths and weaknesses. The whole video collected from fixed point nocturnal bird surveillance is typically viewed at real-time speeds or using fast-forward. This is a time-consuming process and is prone to human bias and errors.

This research project was aimed at developing and improving nocturnal bird surveys through a number of approaches. Knowledge and experience gained through the duration of the doctorate have been used in a number of the sponsoring company's ventures (RPS). The project has also been supported by a steering group consisting of stakeholders involved in bird conservation.

Aims and Objectives

The overall aim of this Engineering Doctorate project was to develop and improve the accuracy, efficiency and application of nocturnal bird surveys using thermal imagers and image intensifiers. This aim was met by the following objectives with a summary of method and findings.

Objective 1: Review current nocturnal surveillance approaches for monitoring bird activity, particularly visual-based methods

A literature search was carried out to assess currently used techniques for monitoring nocturnal bird activity and approaches that could be used to improve the process. The search revealed that although some methods existed, choice of technique depended on the type of data required. The review also highlighted areas for investigation.

Objective 2: Extend the understanding of the strengths and limitations of both thermal imagers and image intensifiers in different conditions for bird surveillance at night

Empirical data were collected from both field trials and surveyor interviews on thermal imagers and image intensifiers. As well as obtaining information on equipment strengths and weaknesses, quantitative information on operating ranges and the effects of varying operating conditions were determined.

Objective 3: Propose a new method for nocturnal bird survey analysis and compare with a typically used review method

Two methods using a surveyor were used to see how a typically used nocturnal survey video review method compared with a proposed new method. The proposed new method was found to be more accurate at detecting flying fauna targets. It was also found relative target size and flight speed across the camera field of view affected detection likelihood using the typical method.

Objective 4: Trial the application of motion detection techniques to improve the efficiency of nocturnal bird surveillance video review

A typical nocturnal survey video review method using a surveyor was compared with a background subtraction and cumulative image differencing techniques. Both automated techniques were found to be more efficient at detecting motion compared to the typical approach.

Objective 5: Explore the application of existing periodicity detection techniques for flying fauna

Two periodicity detection techniques based on area-based differencing using similarity matrices and feature analysis using an image transform were assessed for suitability in detecting bird wing oscillations. Area-based differencing was found to perform this task the best. The application of synthetic and real cyclic data to similarity matrices were found to generate distinct matrices that could be used for bird species classification.

Objective 6: Investigate a method for identifying bird species based on temporal changes during flight

Additional similarity matrices for different bird species groups were generated for testing two classification techniques. The first classification technique was based on cross correlation using a kernel extracted from the some of the matrices. This approach was found not to perform well. The second classification technique was based on reducing the bird similarity matrices to factors sorted by magnitude using singular value decomposition. These factors were used as training vectors for a feed-forward neural network. This approach worked well and was able to classify to some degree between two species groups of birds (large gulls and Gannet) based on wing oscillations.

Contributions to Knowledge

The main contributions to knowledge identified from the work contained within this thesis are identified as follows.

Development of a framework to aid method selection of night vision equipment in nocturnal bird surveillance

Current knowledge of the use of night vision equipment for nocturnal bird surveys has been extended empirically by conducting field trials in varying conditions and through interviewing experienced bird surveyors. This knowledge can be used to select the most suitable approach for bird surveillance at night, depending on the survey aims.

Creation of a method to improve the efficiency and accuracy of the analysis of nocturnal thermal imager video

It has been shown that reducing the review speed of nocturnal bird surveillance video significantly increases the number of flying fauna targets detected by a human observer. Relatively small and fast moving targets have been shown to be factors that cause a reduction in target detection. Adaptive background model subtraction and cumulative frame differencing can be used to improve the efficiency of motion detection compared to a human surveyor.

Creation of a method to identify bird species from wing oscillations using inter-frame similarity matrices

It has been shown that area-based differencing periodicity detection using similarity matrices can be used to detect bird wing oscillation (Lazarevic *et al*. 2007, Lazarevic *et al*. 2008). Perception tests show that some bird species can be identified by their similarity matrices. Bird species classification can be automated using singular value decomposition of these similarity matrices, combined with a feed-forward neural network.

Conclusions

As image intensifiers and thermal imagers have operational differences, each device has associated strengths and limitations. Overall, empirical work established that image intensifiers are best used for species identification of birds against the ground or vegetation. Thermal imagers perform best in detection tasks and monitoring bird airspace usage.

The typically used approach of viewing bird survey video from remote sensing in its entirety is a slow, inaccurate and inefficient approach. Accuracy can be significantly improved by viewing the survey video at half the playback speed. Motion detection efficiency and accuracy can be greatly improved through the use of adaptive background subtraction and cumulative image differencing.

An experienced ornithologist uses bird flight style and wing oscillations to identify bird species. Changes in wing oscillations can be represented in a single inter-frame similarity matrix through area-based differencing. Bird species classification can then be automated using singular value decomposition to reduce the matrices to one-dimensional vectors for training a feed-forward neural network.

Further Work

A number of potential areas for further work have arisen during the life of this engineering doctorate project. From a practical surveillance perspective, additional field simulations should be undertaken to test how thermal imaging and image intensifying equipment perform at detecting airborne targets, in addition to experimenting with different landscapes. Feedback from these trials can be rapidly fed back into further improving surveyor knowledge of how the equipment operates. This knowledge can be used to further enhance nocturnal bird data collection. This is likely to be a continual progress as the sophistication of night vision technology improves over the coming years.

There is an interest in understanding bird and wind turbine interaction, requiring these structures to be monitored. Rotating wind turbine blades can trigger most motion detection approaches. The most straightforward approach to prevent this is by masking the affected area. It is recommended that there is further research into suppressing motion detection caused by moving turbine blades using adaptive approaches.

An introductory approach to identifying bird species in flight has been presented in the research, and initial results have been promising. Some bird species have been identified as having similar inter-frame similarity matrices whilst in flight. Specific trials are recommended to collect large data sets of different bird species whilst in flight. With this additional data, a better understanding of which birds can and cannot be identified with this approach, and the level of identification certainty with those that can.

Publications and Conference Papers

The following publications and conference papers can be found in Appendix A.

Lazarevic, L, Southee, D, Harrison, D, Osmond, J, Frost, D, Wade, M. 2007. Approaches to measure wing beat frequencies with computer vision. *Proceedings of the 5th International Conference on Design and Manufacture for Sustainable Development, Loughborough, UK*

Lazarevic, L, Ward, R, Wade, M, Harrison, D, Southee, D. 2008. Can templates based on similarity matrices be used to identify Golden Plover? *Proceedings of the Annual EngD conference, Guildford, UK*

Lazarevic, L, Harrison, D, Southee, D, Wade, M, Osmond, J. 2008. Wind farm and fauna interaction: detecting bird and bat wing beats through cyclic motion analysis. *International Journal of Sustainable Engineering*. 1:60-68

Chapter 1: Introduction

This chapter provides the background to the project, motivations for the research and an overview to the successive thesis chapters.

1.1 The Importance of Nocturnal Bird Surveys

Due to their importance for the environment, birds are protected various UK and European legislations such as: the Wildlife and Countryside Act 1981; the European Commission Council Directive 79/409/EEC on the Conservation of Wild Birds; the Conservation Regulations 1994; and the Planning Policy Statement 9 Biodiversity and Geological Conservation. Hence any new developments must assess whether they may endanger birds or alter their habitat.

1.1.1 Nocturnal Bird Activity

In addition to familiar nocturnal predatory species such as owls and nightjars, many other bird species utilise the night time for activities including feeding, inter habitat movement and migration. Large numbers of waterfowl and wader species are active at night, often taking advantage of increased food availability or the pattern of changing tides. Night brings the opportunity for some of these species to feed in the absence of diurnal predators (Gillings *et al*. 2005, Mouritsen 1994, Sitters *et al*. 2001, Robert *et al.* 1989), or there is greater availability of prey (Evans 1987, McNeil and Robert 1988, Mouritsen 1994). For example, wader species such as Lapwing *Vanellus vanellus* feed at night to balance their energy budgets (Sheldon et al. 2004). Redshanks *Tringa totanus* have been found to forage for food more at night than during the day (Burton and Armitage 2005), and other shorebird species have been observed foraging at night (McNeil and Robert 1992). Waterfowl may move from one waterbody to another at night (Guillemain *et al*. 2002) and this period allows for better feeding opportunities compared to during the day (Sitters *et al*. 2001). Bird groups such as passerines (e.g. Schmaljohann et al. 2007), waders (e.g. Gudmundsson 1994), geese (e.g. Alerstam et al. 1993) and ducks (e.g. Flock 1973) migrate at night.

For smaller birds (warblers, flycatchers, chats and thrushes) that actively feed during the day, migrating at night is more practical, using the daylight hours to replace energy used during flight and to rest (Alerstam 1990, Lincoln 1935). Migrating during the day would likely force these birds to wait through the night until daylight to feed (Lincoln 1935). Perhaps surprisingly, lighting conditions are not a critical factor for some migratory species (Zehnder *et al.* 2001, Alerstam 1990). Many ducks, geese, gulls, waders and swans will migrate either at day or during the night (Alerstam 1990). Another reason why birds may favour migrating at night is to take advantage of the cooler weather, easing heat dissipation (Kerlinger and Moore 1989), and/or to reduce the risk of predation (Evans Ogden 1996).

1.1.2 The Effects of Man on Birds

As with humans, poor lighting conditions can make movement more hazardous to birds. Low clouds, moonless nights and heavy fog can substantially reduce the distance birds can see (Richardson 1998). This becomes particularly dangerous for birds when man-made hazards, such as communication towers, guy lines, masts and wind turbines lie in a bird's flight path. For example, the poor weather can obscure a bird's vision, and they are unable to see the threat until the very last moment, sometimes perceiving the threat too late. Low cloud can also alter flight height, with migrating birds flying lower under these conditions (Richardson 1998).

Migrating birds move in large numbers and tend to concentrate around land features such as ridges and shorelines. These regions tend to be popular locations for wind farms (Bairlein 2004, Bruderer and Liechti 1998, Akesson 1993). Bird flocks migrating at night have been observed to be more likely to enter wind farms than during the day (Desholm and Kahlert 2005).

Collision risks with turbines are highest during dark nights or nights with poor weather (Winkelman 1995, Dirksen *et al.* 1998, Desholm 2005a). In poor weather conditions birds are forced to fly at lower altitudes and are more likely to be flying at the height of the rotor blades, cables and guy-wires (Drewitt and Langston

2006, Shamon-Baranes *et al.* 2006). Larger birds are at greater risk as they have reduced manoeuvrability (Garthe and Huppop 2004). Collision is not the only concern presented by wind turbines, with loss of habitat, disturbance and barrier effects affecting bird usage of the area (Drewitt and Langston 2006).

Nocturnally migrating songbirds are most susceptible to collide with lit towers in poor weather where visibility is low (Manville 2000). It is suspected that the largest cause of collisions is due to illumination used on tall towers (Beason 1999), whereas during clear nights, tall illuminated towers do not appear to have an impact (Larkin and Frase 1988). In periods of poor weather and low cloud base, birds have been observed to circle around illuminated towers (Cochran and Grabber 1958, Avery *et al.* 1976). Fatalities are not limited to collisions with the tower or support guy wires, but also through sheer exhaustion (Larkin 1999).

Roads and airport runways also pose risks to birds. Roads can lead to fatalities through collision (e.g. Ramp *et al*. 2005). Roads can also affect bird densities, with numbers decreasing towards road edges (Reijnen et al. 1996). Areas surrounding the runway can offer foraging and nesting sites (Kershner and Bollinger 1998). These areas can be hazardous to birds as they may collide with aircraft whilst moving around, resulting in death and potentially catastrophic damage to the plane (Sodhi 2002).

Since these intrusions on the landscape can pose such hazardous situations there is a legal requirement within the United Kingdom that appropriate assessments are pursued to predict potential risk to birds. As part of a European Union directive, Environmental Impact Assessments are the mechanisms used during the proposal stage of a development (DCLG 2000) to assess potential risk.

1.1.3 Limitations of Diurnal Assessments of Nocturnally Active Birds

Diurnal surveys are commonly used to determine the presence of birds, their behaviour and distribution and to predict these factors at night over a given area (Gillings *et al.* 2005). This approach can be misleading, with wildfowl and wader species observed using different land and habitat types, contrasting foraging behaviour and different flock densities at night compared to during the day (Burton and Armitage 2005, Gillings *et al.* 2005, Mouritsen 1994, Sitters *et al.*, 2001, Townshend *et al.* 1984, Robert *et al.* 1989). As a consequence the importance of specific areas and airspace to these birds can be underestimated by only using diurnal surveys (Burton and Armitage 2005). Nocturnal surveys are essential to understand the significance of a given area to nocturnally active birds.

Many regulatory bodies and ecological stakeholder groups are aware of these discrepancies between diurnal and nocturnal behaviours. Should a bird of conservation concern that is active at night be observed during an initial assessment of a site, it is likely that a regulator will insist on appropriate nocturnal monitoring.

1.2 Summary of Overview

Birds have a vital role in the maintenance of ecosystems and the general health of the environment. There are numerous reasons as to why diurnally active birds also utilise the night, from feeding strategies to advantages gained from nocturnal migration. The night can bring fewer predation risks, additional feeding opportunities and the opportunity to migrate safely.

The intrusion of man on habitats utilised by birds has a noticeable effect. Artificial lighting has changed some species of bird behaviour. Manmade structures can have a catastrophic impact. In periods of poor weather and darkness the risk posed to birds by these structures comes from being unable to see the risk, or the illumination produced attracting birds away from their flight path. Both these situations can cause death either through direct collision, or though exhaustion.

Diurnal assessments alone are not enough to understand how nocturnally active birds are likely to behave at night. It is vital that appropriate nocturnal bird surveillance is undertaken to minimise potential impacts of manmade structures on birds.

1.3 Motivation

The initial motivation for this project arose from environmental consultancy RPS's involvement in a nocturnal bird surveillance project. A site in Cyprus was monitored for many nights to ascertain the potential risks of the proposed construction of a tall communication tower on birds using the area. A thermal imager was coupled with a video recorder and hundreds of hours of thermal imaging footage collected. The time, effort, concern regarding accuracy and coordination of the video analysis motivated RPS to seek a more efficient way of processing such video. The initial aim was to improve this approach by automating motion detection; process the bird surveillance video and present the expert ornithologist with 'highlights' to identify and interpret. The project has since evolved into other areas. Little standardisation of nocturnal bird surveillance approaches exists, mainly due to the lack of equipment and survey strategy information available. Although this is not directly related to improving the analysis of nocturnal survey data, choosing appropriate bird surveillance equipment and understanding the strengths and limitations of these implements is likely to improve the accuracy and effectiveness of nocturnal bird surveys. There is also an interest in being able to identify what bird species is being observed. This valuable information is not useful for identifying birds in a specific surveyed location, but could assist in determining areas and altitudes used by that flying fauna.

This overall project sought to improve the efficiency of nocturnal bird surveillance using night vision equipment. This is a challenging aspect – a wide field with many facets. There is a need to comprehend the requirements and demands of the field ornithologist. Many challenges have been encountered in the field to gain necessary experience as well as developing knowledge about the equipment. In addition, understanding was developed about how to optimise the value of the equipment, as well as looking at the application of viable computer vision techniques. Thesis Statements and Chapter Overview

The following two thesis statements (*in italics*) have striven for an integrated approach, the combined elements themselves creating new knowledge and valuable, practical techniques for nocturnal bird surveillance. The following paragraphs outline the chapter contents and which ones support each of the thesis statements.

A framework can be developed for the systematic use of infrared thermal imaging and image intensifying in nocturnal bird surveillance

Thermal imagers operate by detecting heat whilst image intensifiers collect and amplify available light photons. As both pieces of equipment have different functionality, it is likely that depending on the task one will outperform the other. Despite this, there is a lack of empirical comparative research to determine the strengths and weaknesses of thermal imagers and image intensifiers for bird surveillance.

As part of the literature review, Chapter 2 reviews commonly used existing techniques for the remote surveillance of birds, with a focus on the use of night vision equipment. The review also highlights that little work has been carried out to empirically compare both image intensifiers and thermal imagers side-by-side for remote bird surveillance. Chapter 3 emphasises the lack of guidance from UK regulators over equipment choice and outlines an example of poor stakeholder awareness with respect to suitable nocturnal bird surveillance approaches. Chapter 3 follows this by providing empirical quantitative and qualitative studies of both night vision devices trialled side-by-side under a number of real field situations.

Using motion detection software improves the process of reviewing video from fixed-point nocturnal surveillance. This systematic approach reduces the amount of time required for video analysis and removes human biases such as boredom and fatigue.

Chapter 4 examines a typically used manual-based approach for assessing nocturnal video and compares it against an alternative manual-based approach. The impact in flying fauna detection rates by using these two different approaches is examined, with the exploration of effects of relative target size and speed crossing the camera's field of view. Chapter 5 presents two computer-based motion detection techniques one of which is based on a continuously updating adaptive background that copes with gradual changes to the camera's field of view. These automated techniques are compared against a human observer to assess differences in motion detection rates.

The oscillatory, flying motion of birds can be used to classify different species in an automated computer vision system

Apart from radar research, little has been done to capitalise on using uniqueness in bird wing oscillations to identify species groups. This thesis works on the concepts of periodicity and cyclic motion classify bird locomotion. Chapter 6 explores these concepts by looking at how the oscillatory wing movement by flying fauna can be detected through periodicity analysis techniques. Chapter 7 extends this further by assessing how inter-frame similarity matrices generated through area-based temporal differencing can be used to classify bird species through observer perception tests and distinguishing bird species through automated techniques.

Chapter 8 summarises conclusions drawn within the thesis and highlight areas for further work.

Appendix A contains journal and conference papers that are accepted or under review.

Appendix B summarises literature and a small trial to estimate bird surface temperatures used in Appendix C.

Appendix C shows the method used for constructing heated and non heated bird targets for Chapter 3.

Appendix D contains the ornithology surveyor's interview transcripts used in Chapter 3.

Appendix E provides general thermal imager equipment and surveillance information that supports Chapter 5.

Appendix F is the perception test sheet used for Chapter 7.

Chapter 2: Nocturnal Survey Methods and Possible Automation Approaches: A Review

2.1 Introduction

The literature review contained within this chapter consists of two specific themes: examining available methods for nocturnal bird surveillance and exploring appropriate computer vision techniques for improving visual-based surveys.

2.1.1 Available Methods for Nocturnal Bird Surveillance Overview

There are a number of approaches currently available for surveying bird activity at night. To date, methodologies used to undertake nocturnal bird surveys are almost completely dependent on the surveyor to operate the equipment. This review begins by exploring these manual-based observer methods, going on to consider automated methods for remote surveillance of bird activity, with the emphasis placed on visual-based night vision equipment. Remote sensing methods that are used to monitor other nocturnally active fauna are considered.

2.1.2 Computer Vision Techniques for Improving Visual-Based Surveys Overview

There have been a number of applications of computer vision to improve the efficiency of data collection with nocturnal-based survey methods. Efficiencies considered by this thesis are:

- reducing the amount of data that needs to be analysed by a surveyor;
- differentiating flying fauna from other airborne objects using wing oscillations; and
- identifying bird species groups.

This review focuses on approaches most likely to be suitable for remote nocturnal surveys, based on the scope of thermal imagers for bird surveillance.

2.2 Nocturnal Survey Methods

Surveys used to monitor nocturnal bird activity can be loosely grouped into four categories: visual, radar, acoustic and radio tracking, with the focus of this review based on visual surveillance approaches and minimising bird disturbance during surveillance.

2.2.1 Visual-Based Surveys

Visual-based surveys are commonly used to assess a location for bird activity and numbers. Either conventional means are used (using a telescope to watch birds flying past assisted with moonlight or a light source) more increasingly specialised night vision equipment is used to aid the surveyor (thermal imager and image intensifier). Visual-based survey methods can be manual or part automated. This section focuses on manual approaches. The majority of the nocturnal survey work carried out in the field requires full supervision by a surveyor. The surveyor will keep track of any bird sightings, with only post-survey analysis taking place away from the field. Generally, this category can be broadly grouped into moonwatching and using a ceilometer, and the use of night vision technology.

Moon Watching and Ceilometer

Moon watching involves the use of a telescope looking over a visible section of the moon (Liechti *et al*. 1995). A surveyor counts the number of birds flying over the observed part of the moon, identifying the species and distance if possible. Ceilometer surveys involve the use of a high-powered light beam shone vertically, reducing dependence of a survey taking place during sufficient moonlight. Surveyors count the number of birds passing through the light beam, which appear as white streaks as they pass through the beam (Desholm *et al*. 2004). Both these methods are commonly used for monitoring bird migration (e.g. Williams *et al*. 2001, Bruderer *et al*. 1999, Liechti *et al*. 1995)

Both moonwatching and the use of strong light beams are relatively cheap nocturnal survey methods, requiring very little specialised equipment (Desholm *et al*. 2004). Moonwatching is unobtrusive, but it is difficult to get distance information, and much guesstimation is often needed, with variation depending on the moonwatching experience (Liechti *et al*. 1995). Due to the similarity with both methods, there are difficulties in obtaining accurate distance information with ceilometers as well. Also, using a ceilometer changes bird behaviour (Bruderer *et al*. 1999), which is likely to bias results.

Thermal Imaging and Image Intensifiers

Night vision or infrared devices all operate using different parts of the electromagnetic spectrum. Image intensifiers are sensitive to the visible light and near infrared parts of the spectrum (800-900 nm), whilst thermal imagers operate in the short to long wavelength infrared parts of the spectrum (3-15 μm) depending on manufacture (Rogalski and Chrzanowski 2002) (Figure 2.1 – Keiner 2009).

Image intensifiers are commonly used in manned nocturnal surveys. Like thermal imagers, they are able to operate in low light levels. There is more light available in the near-infrared part of the spectrum (but not visible to humans) compared to visible light at night (Rogalski and Chrzanowski 2002) which aids infrared intensifiers that are sensitive to these photons. There are different generations of image intensifiers: 0, 1, 2 and 3, with generation 4 under development. The higher the generation number, the more sophisticated is the equipment (Allison and DeStefano 2006). As the charged couple device (CCD) is sensitive to near-infrared light (Rogalski and Chrzanowski 2002), infrared lamps can improve the functionality of the image intensifier by providing discrete additional lighting (Kunz *et al*. 2007, Allison and DeStefano 2006, Gillings *et al*. 2005).

Long wave infrared bands are the preferred bands for thermal imagers used for fauna surveillance as they have a higher sensitivity to objects at ambient temperature (Rogalski and Chrzanowski 2002). Both thermal imagers and light intensifiers are highly portable.

Thermal imagers are passive systems that detect heat emitted from objects, thereby not requiring ambient lighting. All objects above 0°K (-273°C) emit thermal energy and this provides a viewable contrast to temperature sensitive focal plane arrays (FPA).

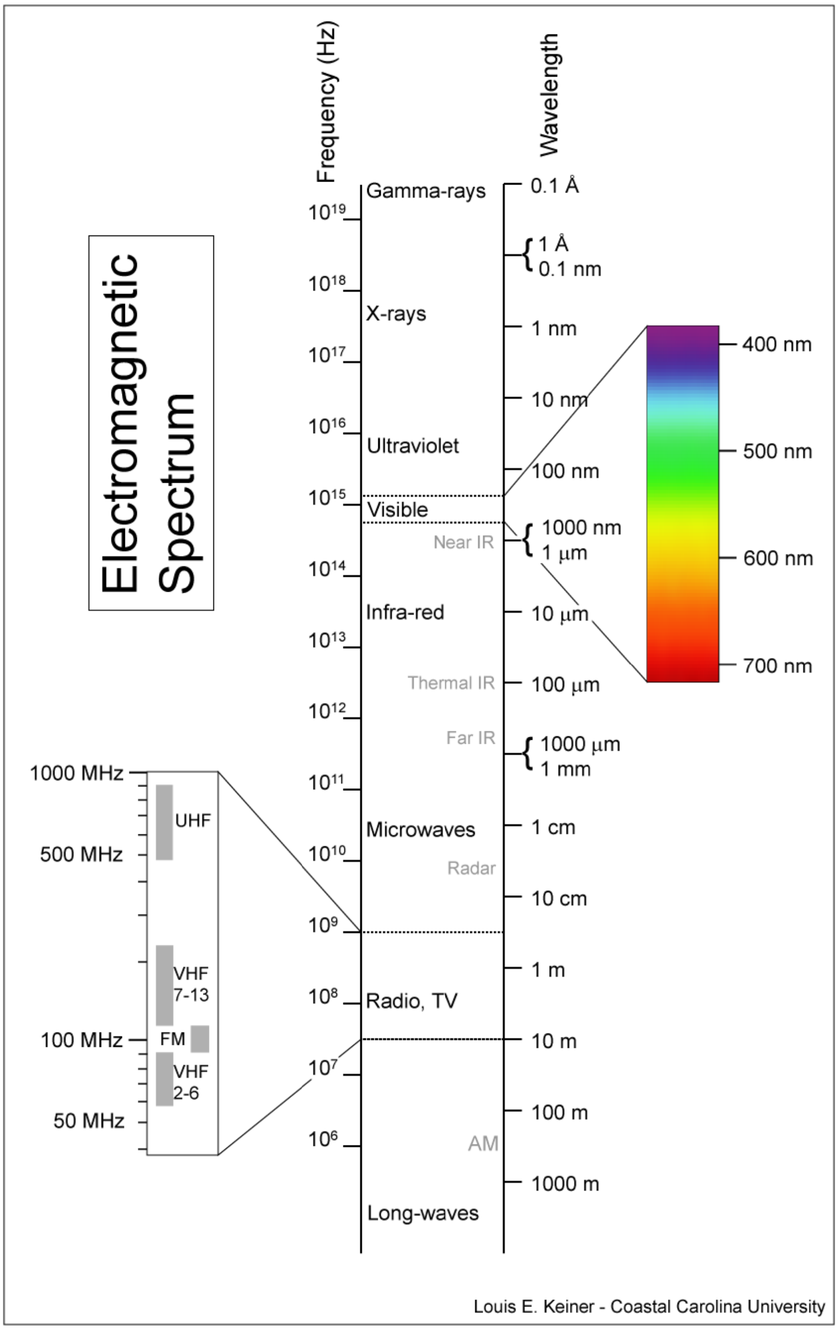


Figure 2.1 Electromagnetic spectrum

The two main bands used for thermal imagers are medium wave infrared (MWIR 3-5 µm) and long wave infrared (LWIR 8-13 µm). LWIR is preferred for applications based in ambient temperatures and operates better in foggy and hazy conditions compared to MWIR (Rogalski and Chrzanowski 2002). Thermal imagers can either be cooled or uncooled (Rogalski and Chrzanowski 2002). Although there is some sacrifice to thermal detector sensitivity with an uncooled thermal imager, they use less power and are lighter compared to a cooled camera.

Using Thermal Imaging and Light Intensifiers on Nocturnal Surveys

Thermal imagers have been used in a number of ecological applications including locating birds' nests (Galligan *et al*. 2003, Boonstra *et al*. 1995), areal surveys of Grey Seal, Harbour Seal and Polar Bear (Cronin *et al*. 2007, Amstrup *et al*. 2004), detecting squirrels, hares, mice (Boonstra *et al*. 1994) and bat counts, monitoring and turbine behaviour monitoring (Horn *et al*. 2008, Sabol and Hudson 1995), and to measure deer abundance (Hermami *et al*. 2007, Belant and Seamans 2000).

Although thermal imagers detect heat, a surveyor can distinguish between birds, bats (Cooper *et al*. 2004) and insects (Zehnder *et al*. 2001) based on the body composition of the flying fauna which is clearly visible from the temperature differences emitted by the target (Kunz 2004). As a result, birds and bats produce a clear silhouette against the sky (Kunz 2004, Desholm 2003, Zehender *et al*. 2001).

Thermal imagers have been extensively used in remote bird monitoring, especially in wind farm surveys. Zehender *et al*. (2001) used a thermal imager to monitor nocturnal bird migration reporting detection ranges of 300 m using a 1.45° lens against a completely clear or completely clouded sky. Video was collected from the imager and video peak store was used to obtain flight lights of birds crossing the camera's field of view. Liechti *et al*. (1995) used a 1.4-1.87° lens to monitor migrating passerines and reported bird detection ranges of 3000 m. Winkelman (1992) used a thermal imaging camera to detect potential collisions between birds and wind turbines. Using a 5° lens ducks were detected up to 3000 m away. Desholm (2003) predicts that the minimum distance required to distinguish an Eider Duck *Somateria mollissima* (based on 5 pixels) using a 7° lens is 260-400 m.

Image intensifiers also have been used extensively in nocturnal fauna surveillance. For example, image intensifiers have been used to monitor nests predated by Badgers *Meles meles* and Red Fox *Vulpes vulpes* (Bolton *et al*. 2007), grazing of deer (Boag *et al*. 1990), and foraging behaviour of Black Bears *Ursus americanus* (Reimchen 1998).

As with thermal imagers, image intensifiers have been used in bird monitoring studies. Winkelman (1992) used image intensifiers to monitor migrating bird interaction with wind turbines. External infrared lamps were used to provide additional discrete illumination. Allison and DeStefano (2006) use a generation 1 and 3 image intensifiers to observe roosting cranes, with cranes positioned up to 300 m away from the imager found to be most efficient for crane surveillance. The generation 3 image intensifier was mounted with a 500 mm lens. Gillings *et al*. (2005) used an image intensifier to understand habitat choice and usage of Golden Plover *Pluvialis apricaria*, detecting birds and mammals at up to 400 m using a 300 mm lens. Close-range monitoring of bird nests have also utilised image intensifiers to understand bird-nest predation (e.g. Bolton *et al*. 2007).

Comparison of Thermal Imagers and Image Intensifiers

Although both thermal imagers and image intensifiers are primed for use at night, due to how each piece of equipment operates they have associated comparative strengths and weaknesses. These factors are grouped as target detection and identification, range and the effects of weather.

For target detection, a single peer-reviewed paper was found that compared a thermal imager and image intensifier side-by-side to detect deer (Belant and Seamans 2000). This study found that in a number of different weather conditions a thermal imager detected significantly more deer compared to the image intensifier. When identifying targets, image intensifiers can provide observable plumage detail (Allison and DeStefano). As thermal imagers detect heat rather than colour only silhouettes are available, and no plumage colourings can be viewed, limiting identification to bird species family on shape alone.

The ability to detect and identify a bird target can be influenced by environmental factors. The ambient temperature of a site during the day and early evenings can sometimes cause difficulties in distinguishing a target from a background using a thermal imager (Han and Bhanu 2005). Difficulties in detecting birds with an image intensifier increase if the plumage of the bird is similar to the scene background (Allison and DeStefano 2006).

Ranges offered by the image intensifier and thermal imager are limited by the laws of optics. There is a trade-off between the range covered by the imagers, the distance of observation, field of view and the size of bird being monitored (Desholm *et al*. 2004). The pixel-resolution of thermal imagers is lower compared to commercially-available photographic equipment. This affects the detection range of a target further when compared with a digital camera using the same field of view. CCD-based image intensifiers will also be affected by this. Multiple cameras can be used to extend the observation range but the current costs of thermal imaging and image intensifying cameras can make this option prohibitively expensive.

Thermal imagers do not require any illumination sources and can operate day and night (Rogalski and Chrzanowski 2002) and are completely independent of light. Image intensifiers still require some ambient lighting to be able to function (Allison and DeStefano 2006). Poor weather conditions such as fog and other visual obstacles limit their operational performance. Dim backgrounds and poor moonlight reduces visibility (Allison and DeStefano 2006, Rogalski and Chrzanowki 2002). An infrared lamp can help extend the detection range of an image intensifier. It can enhance image equality and assist viewing during moonless nights (Allison and DeStefano 2006). As a light source can be reflected off fauna eyes (Belant and Seamans 2000) an infrared lamp can extend the imager's detection range using eye shine. Another consideration is bird disturbance during surveillance. Some bird species are more sensitive to human presence than others, causing them to flush or hide (e.g. Roberts and Schnell 2006). Hence a minimum distance away from a particular bird species may become necessary, potentially reducing visual clarity of the monitored targets.

Poor weather due to precipitation can affect the operation of night vision equipment. Due to how thermal imagers and image intensifiers work, the effect of precipitation on the equipment will vary. All types of thermal imager have the advantage of being able to see through fog, snow, mist and other poor weather elements better than an imaging device that views visible radiation (Desholm 2003, Rogalski and Chrzanowski 2002). Image intensifiers are affected by high humidity (80-90%) which blurs the image output (Allison and DeStefano 2006) and the operator is unable to view past snow and fog (Beland and Seamans 2000). Ambient temperature can also affect an image intensifier. Allison and DeStefano (2006) found that temperatures below 3.3°C caused the lens to suffer from condensation, reducing the effectiveness of their equipment.

Thermal imagers and image intensifiers are portable pieces of equipment that play a key part in monitoring bird activity at night. Thermal imager strengths lie in being more robust to different weather conditions and offering larger target detection ranges. Image intensifier strengths lie in being able to offer the surveyor detailed plumage information for a bird for species identification. A summary of these devices is presented in Table 2.1.

	Thermal Imager	**Image Intensifier**
Strength	Detecting birds	Identifying birds
Lighting	Light independent	Requires ambient lighting. Can be aided by infrared light
Weather	Can operate in snow and fog	Limited by 80-90% humidity Condensation affects operation at <3.3°
Maximum Bird Detection Distance	3000 m with a 1.4-1.87° lens	400 m with 300 mm lens

Table 2.1 Summary of thermal imager and image intensifier features

Although the focus of this project is on night-vision equipment based approaches for surveying, other methods that are used for nocturnal surveillance of birds are presented below.

2.2.2 Radar

The types of radar systems that are commercially available can be classified in two ways, by operating frequency and by operation mode (Desholm *et al*. 2006). Commonly used frequency bands for ornithological monitoring include X-band (8-12.5 GHz), S-band (2-4 GHz) and L-band (1-2 GHz). Operation modes include surveillance, Doppler and tracking radar (Desholm *et al*. 2006). Radar is independent of light and can operate during the day and at night.

Surveillance radars operating in X-band and S-band are commonly used in bird surveillance, especially around wind farms (Desholm *et al*. 2006). Individual birds can be detected within a range of 2-3 km and flocks of birds at up to 10 km (Desholm *et al*. 2004). Birds are detected by monitoring for objects that do not follow wind direction (Koistinen 2000). Species identification can be roughly grouped into songbirds, raptors, shorebirds and waterfowl, determined on the flight speed, target strength, target size and flight behaviour (Cooper 1996).

There are a number of limitations associated with radar for surveying birds based on target detection and identification, range and weather.

There can be confusion with classifying targets. Larger insects tend to fly independently of the wind, and echoes can appear on data received by the radar, causing uncertainty between insects and birds (Cooper 1996). Bats can also be confused with slow flying birds (Desholm *et al*. 2004, Cooper 1996). As radar detects tracks rather than specific birds, a track will not differentiate between an individual bird or a flock flying closely together (Cooper 1996). This is a problem when specific bird numbers using an area is required. Hence visual observations may be required to run in parallel with the radar to determine the number of birds per track and confirm identify of the bird species present (Cooper 1996, Desholm *et al*. 2004).

Although the range of radar can extend thousands of metres, there is a limitation as to how close to the radar objects can be detected. Ground clutter from scene objects such as vegetation, land undulation and buildings can obscure bird targets as much as 25 m above ground (Cooper 1996). Rising and falling waves at sea increases the clutter zone as much as 50 m above sea level (Desholm *et al*. 2004).

This clutter zone is problematic if monitoring birds that are at risk of collision with structures at these altitudes, or surveying species with characteristic low flight altitudes (e.g. Nightjar). Moving objects can also hinder radar's ability to detect birds. A 'shadow effect' (Desholm *et al*. 2004) occurs with a moving object, such as a wind turbine in the range of the radar. This effectively blocks from the radar any activity that occurs around the turbine. Any potential bird collision or avoidance incidents would hence not be visible by the radar (Desholm *et al*. 2004).

Precipitation can also prevent bird detection (Cooper 1996, Desholm *et al*. 2004) due to the relative size similarity of the precipitation and a bird target.

2.2.3 Acoustic Detection

This system, developed by Evans (1998) is based on the use of microphones to follow bird migration by monitoring birdcalls. Microphones are set up at different locations over an area to record calls from migrating birds. The recorded sounds are then analysed by a technician to determine the species of the bird that made the call. As the method is not dependent on lighting conditions, it can operate at night. The system has been tested in New York State, USA, and was found to be able to record at up to 600 metres every direction from each microphone (Evans 1998).

Acoustic detection is likely to be biased against species that call intensively during flight (Dierschke 1989) or move at low altitudes (Desholm *et al*. 2006). As a result, it is possible that bird density numbers are underestimated (Desholm *et al*. 2006).

2.2.4 Radio Tracking

The previous three approaches are non-contact observation approaches for monitoring birds. Radio tracking is an invasive approach that can provide detailed information on an observed target including behaviour, physiology and location. The use of radio tags are seen as the most practical approach for monitoring rarer bird species (Sutherland *et al.* 2004). Radio tracking can produce more in-depth behavioural information compared to visual-based techniques. Details on nest locations, inconspicuous behaviour, and mortality are more readily available with radio tracking (Sutherland *et al.* 2004) compared to visual methods alone.

One of the main disadvantages associated with radio tracking is the need to handle and tag birds. Capturing and tagging the birds may have an impact on their mortality (e.g. Sharpe *et al.* 2009, Cotter and Gratto 1995). The tags also may cause an impact on the bird's behaviour (e.g. Vukovich and Kilgo 2009, Whidden *et al.* 2007, Hooge 1991).

Both radar and acoustic detection cannot provide information on how a bird interacts with structures such as communication towers and wind turbines, rendering these methods unsuitable for monitoring collisions. Acoustic detection requires specialist installation of microphones over a large area, which takes time and does not make the system very portable. Radio tracking has constraints based on bird size in relation to the tags used, and monitored birds may suffer higher rates of mortality. Bird surveillance radar systems are large, bulky systems (once power supply and computers are considered) and are transported on a trailer for land-based surveillance (GMI 2007) or require specialist rigs for offshore work (Desholm *et al*. 2004).

2.2.5 Summary of Visual-Based, Radar, Radio Tracking and Acoustic Equipment

For monitoring bird interactions with structures before and after construction, image intensifiers and thermal imagers are currently the most suitable choice. These night vision technologies can confirm potential bird collisions and are not affected by landscape clutter. Image intensifiers and thermal imagers are highly portable, and can be moved to a variety of locations. In particular, thermal imagers are not limited by moon illumination and both thermal imagers and image intensifiers have been shown not to disturb fauna under observation, although this is dependent on how sensitive the species under observation is to humans, and the distance of the surveyor from the birds. For detailed investigation of individual bird movement in an area, radio tracking can supplement the survey in the above context.

2.3 Automating the Nocturnal Surveillance Process

Relying solely on an observer in the field to scan for nocturnal bird presence can be time-intensive. In addition, accuracy may be affected through the use of different observers, or by the effects of fatigue, boredom and other factors that cause human error. There are also hostile situations such as offshore, or at great heights where bird data needs to be collected. A remote system can reduce dependence on observers out in the field by collecting and processing the data using other means can help reduce the likelihood of errors and help survey difficult locations. There are a number of methods that have been used to achieve this, through recording surveys onto video, collecting this video digitally, to the use of trigger mechanisms to collect images of bird activity.

2.3.1 Reducing Analysis Time through Video Reduction

Video-based remote monitoring of birds over large distances is not uncommon (Allison and DeStefano 2006, Desholm *et al.* 2004). Video from such surveys is typically recorded in full, to be analysed after the survey has been completed (e.g. King and DeGraaf 2006, Saxton *et al.* 2004, Delaney and Grubb 1998, Sykes *et al.* 1995) and the technique is commonly used in ornithological studies (Reif and Tornberg 2006). There are a number of advantages in collecting data in this way, such as:

- avoiding unnecessary disturbance of targets under observation (Delaney and Grubb 1998);
- providing a back-up of events should something happen quickly and the observer misses it;
- reducing the number of personnel required on-site (Sykes *et al.* 1995);
- the video can be reviewed in more comfortable surroundings; and

- different surveyors can take turns to review the video, and breaks can be used to ease the effects of fatigue.

Analogue time-lapse video recorders, used with videocassettes are an inexpensive and popular approach for gathering large quantities of surveillance data.

Once the video data are collected onto videocassette, they are either viewed at the regular rate (real-time speed) or with the use of fast-forward (Desholm *et al.* 2004, Sykes *et al.* 1995). Using fast-forward allows the surveyor to skip through perceived periods of inactivity, reducing the amount of time required to analyse the video (Delaney and Grubb 1998, Sykes *et al.* 1995). However, it is possible that speeding up the video during these periods may cause the observer to miss fast moving and small birds (Desholm *et al.* 2004). It is also possible to slow down the rate at which video is viewed by using a time-lapse recorder. By reducing the speed at which the video is reviewed at, surveyors will have more time to observe fast moving and small targets, which may further increase target detection rates. The reduce-speed method available on a time-lapse video recorder causes the video frames to jump (Sykes *et al.* 1995), and may cause difficulty in reviewing the video, especially if there is a complex background.

Another approach that can be used to summarise video data from thermal imaging is through the use of peak video store (Zehnder *et al*. 2001). Successive video frames are stacked on top of each other, producing flight lines of passing bird targets. A disadvantage with this approach is that it is dependent on either a fully clear or fully clouded sky (Desholm *et al*. 2004). It is unlikely that this approach would be successful against a cluttered scene.

More commonly, video can also be collected digitally, storing collected data onto a computer hard disk. There are also software-based methods that can be used to trigger recording only when an event has been detected, e.g. a bird flying into view. The video is collected digitally, storing collected data onto a computer hard disk. Using a trigger mechanism, a decision is made whether or not the video should be stored. This approach reduces the need for an observer to view large quantities of video, reviewing only events that have been triggered by the software (Desholm *et al*. 2006).

The Thermal Animal Detection System (TADS) is an infrared-based detection system, developed at National Environmental Research Institute (NERI) (Desholm 2003). A thermal imager can be installed on a turbine and frames collected from the thermal imager are fed to a computer on site that remotely transmits the images to a remote computer by fibre optics in the wind turbine. The detection software on the remote machine monitors the data received by the computer for changes in the threshold temperature. TADS is triggered to commence recording when the threshold temperature changes. The TADS system can detect avoidance as well as collisions since it monitors for any movement within the field of view of the camera. Disadvantages with the TADS system include the temperature threshold being sensitive to clouds, setting the system to record and it is reliant on background objects being masked (Desholm 2003). Designed by Verhoef *et al*. (2004), WT-Bird (Wind Turbine-Bird) is an image intensifier system based on an acoustic trigger. Microphones were installed at different points on a wind turbine with an image intensifier set up to face the wind turbine blades. When an impact occurs, the sound of the impact is detected by the microphones and triggers the imager to record images of the collision. Initial trials of this system have proved problematic, with the operational sound of the wind turbines monitored being louder than the impact sound of birds (Desholm *et al*. 2006).

WT-Bird cannot provide any information on near-miss scenarios involving birds and structures, and is not usable for pre-construction site surveillance. It also requires modification to the wind turbines. TADS offers the ability to provide data on how an area is utilised by birds both before the area is developed and after to assess impacts. A key disadvantage with TADS is the inability to adapt to slow changes within the scene it is monitoring. Another limitation is that the TADS system is camera specific using proprietary software. As thermal imaging technology improves and pixel-resolutions get larger, it will not be possible to simply plug in a new camera from a different manufacturer into the current TADS system.

2.3.2 Non-Bird Nocturnal Flying Fauna Detection Systems

The methods used to automate nocturnal bird surveying were found to be similar to those used to census bats. Both methods outlined below used a thermal imager.

Melton *et al*. (2005) produced a system that detects and tracks bats during an emergence survey. A background model is maintained based on taking the modal value for each pixel over the last five frames. The background model is then differenced with incoming frames. A user-specified fixed threshold is applied to determine potential bat ‘peaks’. Peak centres are determined and a motion vector based on the speed at which the peaks move is calculated. The motion vector is then used to predict future positions of the bat peaks, generating tracks to represent individual bats. Melton *et al*. (2005) reported counts that were within 2% of those determined through manual means.

Bekte *et al*. (2007) also use an adaptive background model approach. Each pixel is modelled on a Gaussian distribution based on a number of past frames. The model is differenced with incoming frames and any pixels exceeding a standard-deviation based threshold are tagged as foreground objects. A recursive Bayesian filter is then used to track each of the peak foreground objects. When compared against manual marking of bat tracks, the system matched track numbers within 6%.

2.3.3 Computer Vision Approaches for Motion Detection

There are a number of techniques available from computer vision that can be used to detect motion in addition to those used in trigger-based systems such as TADS and WT-BIRD (Desholm 2003, Verhoef *et al*. 2004). Other more conventional methods for motion detection include background subtraction, temporal differencing and optical flow (Hu *et al*. 2004).

Temporal differencing

Temporal differencing (also known as image differencing) compares how a pixel value varies over a number of consecutive frames (Hu *et al*. 2004) and can be used as a base for other image processing techniques such as temporal templates (Bobick and Davis 2001). Differencing only two frames can result in a lot of noise, clutter and other scene disturbances being identified as foreground objects (Davis *et al*. 1998). The robustness of temporal differencing can be improved through using three consecutive frames (Hu *et al*. 2004).

Background Subtraction

Background subtraction is one of the most popular approaches for motion detection. Usually some form of background modelling is involved, representing the scene without any objects of interest (Yilmaz *et al*. 2006, Hu *et al*. 2004). There are a variety of approaches used to model the background, a popular approach being to model each pixel as a Gaussian distribution (e.g. Betke *et al*. 2007, Lombardi 2001, McIvor 2000, Heikkila and Silven 1999). To provide more robustness in multi-modal backgrounds, Stauffer and Grimson (1999) introduced the concept of multiple Gaussian distributions per pixel. A number of the distributions can represent background objects that may move in the scene, such as a swaying branch or ripples on water. Alternatively, each background pixel can be updated using a Kalman filter (e.g. Gao and Zhou, 2001, Ridder *et al*. 1995) using a temporal median (e.g. Monteiro *et al*. 2008) or a temporal modal value (e.g. Melton *et al*. 2005).

The second stage involves comparing a new frame with the background model obtained. Typically, the new frame is differenced with the model, and either a fixed threshold (e.g. Melton *et al*. 2005, Heikkila and Silven 1999) or one based on variance(s) or standard deviation (e.g. Betke *et al*. 2007, Lombardi 2001, Stauffer and Grimson 1999) is used to determine whether pixels within the new frame belong to the background, or are foreground objects.

Optical Flow

Optical flow motion techniques assess how motion changes an image over time. "Motion fields" represent the movement of objects based on the relative displacement of image intensity values between image frames (Yilmaz *et al*. 2006, Hu *et al*. 2004). Once the motion field has been computed, the measurements of the image velocity can be used for motion detection applications (Barron *et al*. 1994). The advantage of using optical flow methods is that they can be used to segment the image, even if the camera is moving (Sanfeliu and Villanueva 2004). Optical flow methods tend to require large amounts of computational power and hence are unlikely to be suitable for real-time applications using standard computational hardware (Hu *et al*. 2004).

Summarising Motion Detection Techniques

Optical flow approaches are computationally expensive. Temporal image differencing and background subtraction offer two relatively rapid forms of motion detection. Both image differencing and background have been successfully used to analyse bat flights.

2.3.4 Detecting Periodic and Cyclic Motion and Classifying Fauna in Flight

As interest grows in monitoring the effects of such structures as wind farms on flying fauna, there is an ever-increasing need to be able to monitor wind turbines for potential bird and bat collisions. As sharp, sudden movement, such as rotating turbine blades can trigger motion (Hu *et al*. 2004) it is desirable to block them out of the image. The approach used for blocking rotating turbines in an existing bird surveillance system involves masking areas of an image prior to thresholding (Desholm 2003). A limitation arises as it is not possible to view bird interactions with the turbine if the system has not been triggered to record due to the mask.

Apart from radar, very little work has been reported to classify birds by species group whilst in flight. This is quite a challenging problem as flying fauna can change their shape rapidly as they flap their wings to move from one location to another. Radar echoes of flying fauna are used to distinguish between birds, bats and insects (e.g. Schmaljohann *et al*. 2008, Bruderer and Popa-Lisseanu 2005). There are also temporal variances in radar cross-section of flying fauna that could be spatially similar to species group (Schmaljohann *et al*. 2008, Konrad *et al*. 1968). There is a concern raised by Cochran *et al*. (2008) that wing beat patterns of birds can differ between species groups. However this refers specifically to thrushes, and may not be applicable to other bird species groups.

Wing beats of birds can be observed on thermal imagers (Gauthreaux and Livingston 2006, Liechti and Bruderer 1995). As a silhouette can be obtained of the bird as it crosses the cameras field of view over a number of frames, this may be of use in determining bird wing beat oscillation information. There have been several techniques based on detecting periodic, non-rigid motion. These techniques are categorised as follows, according to Cutler and Davis (2000):

- point correspondence analysis;
- pixel periodicity analysis;
- periodic motion feature analysis; and
- object similarity periodicity analysis.

Techniques based on point correspondence

Point correspondence techniques look to see how motion may repeat itself by taking a point or points of an image and then monitor how the point displacement changes across the image (spatial change). Tsai *et al*. (1994) fit a trajectory curve of selected points move over a number of frames. Points are located on joints of a person’s body and are tracked as they move. The curvature of the curve is then calculated by fitting it to a quadratic surface-fitting algorithm. Once the curve has been extracted, autocorrelation is applied to check for any peaks that would reveal periodicity in the motion. Seitz and Dyer (1997) use temporal correlation plots for repeating motion without the use of object tracking. There are features within the technique used by Seitz and Dyer that allows the method to monitor repeating motion, rather than motion with constant periodicity, and can monitor non-rigid objects in motion.

Pixel-level analysis for periodicity

Whereas point correspondence looks at how a specific point varies spatially on a set of images, pixel-level analysis looks at how specific pixels vary temporally over a set of images, i.e. how does a pixel in a certain position vary over time? Polana and Nelson (1997) align objects in a sequence by their centre of gravity and then extract reference curves. Spectral energy is estimated along the curves, and periodicity is measured based on spectral energy differences from the curves. Liu and Picard (1998) track foreground objects, which are then aligned by their centroid, and formed into an image block. An XT slice at the ankle level of the tracked person is taken, and 1D Fourier analysis is applied to the centre column of the slice. The power spectrum and harmonic energy reveal periodic motion.

Periodic motion feature analysis

Methods based on periodic motion are based on identifying features in the image, and then looking for periodicity generated by the selected features over time. Fujiyoshi and Lipton (1998) build a feature model by segmenting the object of interest, and producing a star skeleton from the person's object boundary. Fourier analysis is then carried out on the angle differences produced by parts of the skeleton, and signal correction and autocorrelation is carried out to determine periodicity in the analysed motion. Niyogi and Adelson (1994) use a similar method to Liu and Picard (1998) by focusing on the XT slice at the ankle level of the observed person target but unaligned. Templates are then used to find the distinctive braided pattern in the XT slice. An XT slice consists of the temporal changes of x pixels over time.

Object similarity periodicity analysis

Rather than looking at temporal changes at the pixel level, object similarity periodicity analysis looks at how the whole object changes temporally. This is achieved through comparing the object with itself over time. The technique used by Cutler and Davis (2000) works by aligning an object by its centre of gravity, and then differencing the object with itself temporally. The results are used to produce a similarity matrix. Repetitive, periodic motion is then detected by applying a threshold to a 1D power spectral density. The dark parts of the similarity matrix indicate periodicity within the stack of images. Cutler and Davis apply this approach to people as well as dogs. Plotnik and Rock (2002) also use a similarity matrix using a similar approach to Cutler and Davis (2000). The frequency of the motion is found through applying autocorrelation to the similarity matrix, and then fitting a lattice over the local peaks. Albu *et al*. (2005) also use similarity matrices, but the matrices are generated through segmented and binarised target correlation rather than differencing.

Summary of Periodicity Detection Techniques

A number of the techniques outlined above require locating and tracking certain features to determine periodicity (Tsai *et al*. 1994, Fujiyoshi and Lipton 1998). As birds are free to move in all three dimensions, it is likely to be very difficult to extract and track specific features such as wings. Other techniques rely on fitting curves to the objects being monitored (Seitz and Dyer 1997, Polana and Nelson 1997). When dealing with birds that are a few pixels in size, shape changes between wing oscillations may not be large enough to get an accurate fit from the curves to measure periodicity. Assessing how an object changes over time by comparing the whole object over time (Cutler and Davis 2000, Plotnick and Rock 2002, Albu *et al*. 2005) provides an approach that is more robust to segmentation and object alignment, rather than using a single point (Polana and Nelson 1997), does not require specific tracking of features such as limbs or joints and works well with low resolution video (BenAbdelkader *et al*. 2004). Selecting an XT slice (Liu and Picard 1998) across a section of a flying bird may provide a distinctive pattern identify periodic activity.

2.3.5 Target Identification and Classification

There are a number of approaches that have been used to identify wildlife from either still images or video. These techniques generally are based on natural markings. For example Burghardt and Cambell (2007) provide an approach for identifying and tracking individual African Penguins *Spheniscus demersus* based on their unique chest spot patterns. Van Tienhoven *et al*. (2007) use the markings on Spotted Raggedtooth Sharks *Carcharias taurus* to classify between individuals. Ranguelova *et al*. (2004) use the different shading patterns in Humpback Whale *Megaptera novaeangliae* tails to distinguish between fellow whales. All the above approaches are based on locating specific features on the animal, such as spots or lines. Images and video collected from thermal imaging cameras will have no colour or plumage information of distant bird targets and hence these approaches above are unsuitable.

Bird flight style is commonly used by bird-watchers to identify a flying bird down to individual or species group with wing oscillations providing information (Cornell 2007). Depending on species group, bird flight pattern can vary significantly from species to species. Spatial differences within inter-frame similarity matrices generated object similarity periodicity analysis have been used in visual applications to distinguish between targets. Cutler and Davis (2000) use such matrices to classify objects moving with periodicity as person, dog or other. Periodicity is detected through time-frequency analysis, and classification is achieved through correlating the matrix with itself (autocorrelation) and comparing the peaks with a pre-specified 2-dimensional lattice. With a data set containing 89 incidents of dogs, persons or vehicles Cutler and Davis (2000) report a success rate of 100%. BenAbdelkadar *et al*. (2004) use the spatial variances within a similarity matrix to classify people based on their walking style. BenAbdelkadar *et al*. (2004) used samples of volunteers walking at different angles in front of the camera and reported classification success rates of 70% on a data set of 54 people walking in parallel with the camera.

In addition to the classification approaches used by Cutler and Davis (2000) and BenAbdelkadar *et al*. (2004), neural networks are popular for target identification as they are not dependent on prior problem information (Jain *et al*. 2000) and are relatively straightforward to use. Feed-forward neural networks are commonly used in classification tasks (Jain *et al*. 2000). Neural networks have been used to detect the presence of pest birds (Nadimpalli *et al*. 2006), classify weeds (Tobal *et al*. 2008), distinguish between leopard faces (Cross *et al*. 2005) and detect predetorial animal hunts in wildlife video (Haering *et al*. 2000). Overall, neural networks offer a flexible approach for dealing with target classification errors, without depending on large amounts of task-specific details (Jain *et al*. 2000).

2.4 Discussion

To support the problem domain outlined in Chapter 1, an overview of currently used and related nocturnal survey methods for flying fauna have been presented. Further information on night vision equipment has been provided, along with applications in the ecological world. A review of methods that could be used to increase the efficiency of nocturnal bird surveys, along with potential approaches to automate species group identification has been provided.

2.5 Conclusion

The review presented in this chapter has highlighted some areas for investigation, namely:

- defining a methodology for equipment choice;
- overcoming inefficiencies associated with unnecessary (proportions of) video viewing; and
- consideration of computer vision techniques to improve survey efficiency.

The following chapters look to address some aspects of these opportunities.

Chapter 3: Calibrating an Image Intensifier and an Infrared Thermal Imager

3.1 Introduction

There has been a steady growth in the use of night vision equipment in the surveillance of nocturnal faunal activity. Night vision equipment can help support human eyesight in darkness, enhancing our ability to investigate and understand the nocturnal behaviour of animals such as bats, badgers and birds. The most commonly used night vision technologies for surveying and studying birds are thermal imaging cameras (also known as forward-looking infrared cameras (FLIR)) and image intensifiers (also known as light intensifiers and nightsights[1]). As with most technologies, night vision equipment continuously improves and develops and such trends have made thermal imagers and image intensifiers attractive for non-military applications, such as those within ornithology.

As outlined in the literature review, thermal imagers and image intensifiers have been used in a number of applications relating to nocturnal bird monitoring. These include monitoring bird interactions with man-made structures, bird nest predation, nocturnal activity and bird migration.

Aside from research interests, awareness of potential bird conflicts with manmade structures is important for impact assessment, especially at night when the risk of collision is considered to be higher than during the day (Winkelman 1995, Dirksen *et al.* 1998, Desholm 2005a). The application of nocturnal methods such as those described in the literature review are still relatively novel with respect to their use as a tool for assessing potential avian impacts of manmade structures. With respect to impact assessments, there is still a failure by regulators to standardise when to engage in nocturnal bird surveys, and how this is approached.

[1] Explicitly, nightsight usually refers to the imaging device attached to a rifle that both provides the user with a view of the target and includes a graticule crosshair, light spot or other adjustable mechanism that indicates the point of aim of the rifle. Nevertheless, nightsight is also used to refer to an image intensifier.

This probably reflects a lack of general awareness as to the availability and capabilities of night vision equipment and best use practice. Currently in the UK in relation to wind farm impact assessments, only Scottish National Heritage (SNH) provides some degree of guidance and expectation of nocturnal surveillance for certain species of birds, although this is based on image intensifiers alone (SHN 2005). The lack of guidance from regulators generally, combined with the number of techniques from which to choose can cause confusion when deciding on the most appropriate method to use. An example of this arose during a need to monitor for presence/absence of Nightjar feeding at a site (Ellis and Lazarevic 2006). Initially, the Royal Society for the Protection of Birds (RSPB) recommended the use of radar to monitor for nocturnal Nightjar activity (NSDC 2006). As was reviewed in Ellis and Lazarevic (2006) it would be unlikely for Nightjars to fly above the ground clutter zone of radar with any regularity, rendering this approach inappropriate. Another technique, using both a thermal imager and image intensifier was presented to relevant stakeholders, and was accepted as a more appropriate approach (Ellis and Lazarevic 2006).

Although thermal imagers and image intensifiers overcome some of the limitations that affect radar, when compared against each other, these surveillance tools have associated advantages and disadvantages.

The principle aim of this chapter is to extend understanding of the strengths and limitations of both thermal imagers and image intensifiers for bird surveillance at night. This was achieved empirically through side-by-side field trials of a thermal imager and image intensifier and by interviewing experienced nocturnal ornithological surveyors.

The field trials sought to examine how moonlight and target shading affect image intensifier operation. In addition, the field trials compared a thermal imager with an image intensifier, side-by-side in a simulation of a nocturnal bird survey. By using artificial targets that remain constant, over fixed distance intervals, the field trials were repeatable. For birds that are free to roam, it may prove difficult to estimate their distance away from the camera. Allison and DeStefano (2006) measured the distance between observed target (cranes) and image intensifier position the following day. The distance was measured between the estimated centre of the crane roost (based on scat remains and fallen feathers) and where they remembered their vehicle to have been the previous evening. Desholm (2003) used a more accurate approach for calibrating his thermal imager by using a caged chicken and pheasant at different distance intervals away from the imager. This allows for detection distances to be more accurate, but is only based on two birds of similar size. To produce an experimental setup with greater variation in bird target size and plumage shading, it is likely that the capture and temporary caging of wild birds would be necessary. For this, a specific research license from the relevant agency (Natural England in England) would be required, adding unnecessary bureaucracy.

Interviewee opinions were sought on the strengths and weaknesses of thermal imagers and image intensifiers, and how to choose the most appropriate tool for nocturnal bird surveillance. The transcripts for the interviews are in Appendix D. The field trials focussed on how an image intensifier was affected by target shading and celestial illumination; how an image intensifier and thermal imager compare under similar circumstances; and how target size affects detection and identification distance for both pieces of equipment. They were not able to address other situations that may be encountered during nocturnal bird surveillance, such as artificial lighting and changes in weather, and hence the interviews were used to draw upon the surveyor's previous experience. The knowledge achieved from the field trials and from the interviews was brought together and used as a base for developing and improving future nocturnal bird surveillance methods based on night vision equipment. These developments and improvements have been brought together to form RPS's standard operating procedures for nocturnal bird surveys.

3.2 The Influence of Ambient Light and Target Shading on Image Intensifier Operation, Compared against a Thermal Imager

3.2.1 Introduction

As identified previously, there are a number of factors that can affect the ability to detect a bird target including: target size, shading and location. As in standard optics, depending on the magnification and distance, the smaller a target is, the harder it is to detect. Target shading can affect the likelihood of detecting a target with an image intensifier, depending on the background. Water, mud, woodland and open areas can all affect the appearance of a bird. Allison and DeStefano (2006) experienced variances in target detection depending on plumage shade. Other factors, such as reflected bird eye shine and target shape also influence detection and identification. Thermal imagers operate on detecting thermal contrast, so target colouring is irrelevant. Hence shape and size are features used to detect and identify a bird (Desholm *et al*. 2006).

Using live bird targets to test these factors present problems including welfare and positioning the birds. Custom-made targets were constructed in different shadings and sizes, with some of the targets being equipped with heating systems to test the thermal imager. This allows for the representation of different bird species encountered in the field (rather than just two used by Desholm (2003)), and the pre-determination of accurate distances between the targets and the night vision equipment (rather than guessing start and end points post surveillance (Allison and DeStefano 2006)).

The field trials consisted of three separate tests (corresponding to Table 3.1):

1. determining which targets could be detected/identified in known positions;
2. target detection rates whilst changing target locations; and
3. the effects of using the hyperfocal distance on the thermal imager on target appearance.

3.2.2 Methods for Trialling Equipment Side-by-Side

The field trials were carried out over a total of four nights; two on or near a full moon, and two on or near a new moon. Details of the field trials, including dates, surveyors present, moon phase, weather and method(s) used have been outlined in Table 3.1.

Date	Surveyors	Moon	Weather	Methods (Section)
18/08/08 @23:00	AB, AS	2 Days after Full Moon	50% Cloud at Times, Medium Breeze	1,3
15/09/08 @23:00	NG, RW	Full Moon	Clear	1,3
28/11/08 @04:00	NG, RW, AB	New Moon	Clear, Fog @05:45	2
03/12/08 @23:00	NG, RW	6 days after New Moon	Overcast	1,2

Table 3.1 Details of field trial

Different moon phases can affect the operation of image intensifiers i.e. in relation to ambient light levels. An infrared light source can provide a discreet, additional lighting for image intensifiers. Gillings *et al.* (2005) report with the combination of a 300 mm lens fitted to an image intensifier and a 1-million candle-power lamp with infrared filter, they were able to detect birds to 400 m. To see to what extent an infrared light source can aid target detection, an infrared lamp was also trialled with the image intensifier.

The Targets

A total of nine targets, with differing shadings and sizes were constructed for the side-by-side field test (Figure 3.1). The aim behind the design of the targets was to represent a number of situations expected in field conditions. These included different bird sizes and bird shading, with some of the targets heated to represent body heat for the thermal imager.

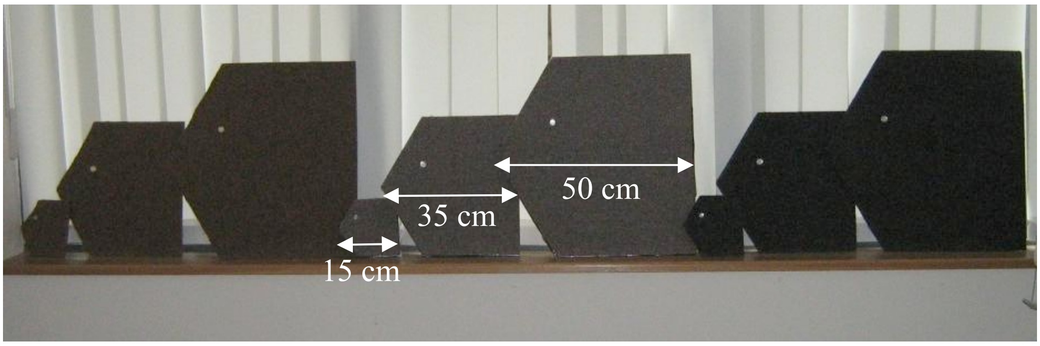


Figure 3.1 Shape, sizes and shades of targets

The smallest targets (15 cm) represented waders such as Dunlin and Golden Plover, medium sized targets (35 cm) represented wildfowl such as Pochard and Tufted Duck, and large targets (50 cm) represented geese such as Pink-footed and Greylag Geese (sizes are based on values from Svensson and Grant 2001). Three different shades, differentiated for the purpose of the field trial as light, medium and dark, were used to represent different bird plumages. Three of the targets had heating systems to mimic bird body heat. To understand the relationship between bird surface temperature and ambient temperature, a literature search was undertaken and field data were examined. Details of this can be found in Appendix B. As bird shape and eye-shine (when using an infrared lamp) are used by field ornithologists to detect and identify birds with night vision equipment, shape was represented with an arrowhead in all of the targets, and a reflective button was attached for eye-shine (Figure 3.1). The targets were attached to individual metal rods using high-strength spring clips. To provide power for heating the targets, gel lead-acid batteries were used, with insulation placed in front of them to obscure them from the thermal imager. Full details on the construction of the targets can be found in Appendix C.

Detecting and Identifying Targets in Known Positions

The targets were spaced approximately 80 cm apart. The target order was determined by shading (medium, light, dark) and then by size (small, medium, large). All arrowheads pointed to the left (Figure 3.2).

Figure 3.2 Installed targets (light-shaded targets are heated. Lead-acid batteries are below (insulation screen not yet in place))

The comparison trial was conducted at Jubilee Park football grounds, Huntingdon (Figure 3.4). Jubilee Park was chosen as there was comparatively little light pollution, with the majority of light coming from the moon and stars. For the visits of 27/11/2008 and 03/12/2008, the opposite end of the field was used for the trials. To check for background consistency, both target locations were inspected by an ornithologist surveyor. It was judged that both backgrounds for the target locations were similar enough to be classed the same (Figure 3.3).

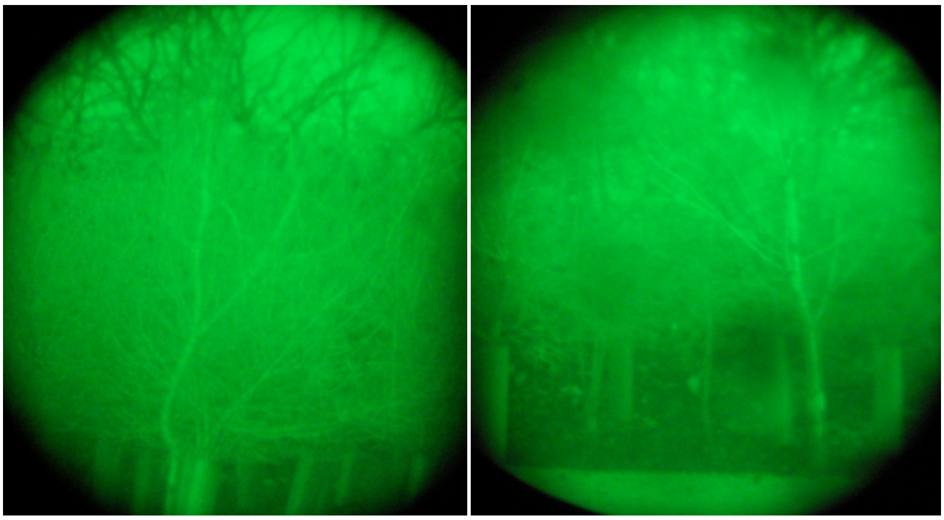


Figure 3.3 Pictures through image intensifier of each field end

Markers were placed at 25 m intervals in a straight line from the decoys (Figure 3.4). A total of 12 intervals were used, totalling a distance of 300 m.

Figure 3.4 Arial image of the field test site. Targets at yellow marker, 25 m intervals marked in white

The thermal imager used was a FLIR ThermaCam P60 with a 12° lens for x2 magnification. The imager was mounted onto a tripod for ease of use. The image intensifier used was a Thales Maxi Binokite with x6 magnification. The infrared lamp used was a Cluson Clulite 1M candlepower torch with a Cluson A5 infrared filter (Figure 3.5).

Figure 3.5 Image intensifier with infrared lamp and thermal imager in use

A total of four surveyors were used for the full moon field trial (Table 3.1). Three surveyors were present for the new moon field trial on 27/11/2008, but fog hampered the completion of the trial. Two surveyors were available for the successfully completed new moon trial that took place 03/12/2008. The reason behind surveyor number variance was due to surveyor unavailability. All the surveyors had good experience of using the image intensifier, all observers having used an image intensifier for surveying purposes on at least two long-term projects. For the thermal imager, a demonstration was given to those unaccustomed to using it. In addition, verbal instructions on how to focus and zoom the thermal imager and adjust the temperature range were provided.

Starting at 25 m from the targets, and moving 25 m further away at each interval, the surveyors stated which targets they could detect and identify, the information being recorded on pre-printed data collection sheet. Detection was defined as being able to see the target, but unable to determine the shape. Identification was defined as being able to detect and recognise the shape of the target. Surveyors using the thermal imager focussed onto the targets and reported what they could see. They first used it to determine what they could detect and identify, and then had a second pass with the image intensifier, supported by the infrared lamp to repeat the process.

A limitation emerged with the initial layout of the targets. As the supervisors were aware of target ordering, this was not a blind trial. It was possible that either the surveyor ‘detected’ a target he may not have spotted in real field situations, or conversely dismissed a target he felt he may not have detected in field situations which he may well have spotted. This was handled to some degree by using more than one surveyor for the field trials.

During the first field tests during full moon (Table 3.1), the surveyors commented that the small heated target provided a heat profile that resembled one that would be observed for a bird target with a thermal imager. The medium and large heated targets based on the heated plates (see Appendix C) failed to accurately represent expected bird heat profiles. Consequently it was decided to modify the medium and large target. The heating system used in the small heated target was replicated and scaled up for the medium and large heated target. The new heating systems were used for the field trials carried out on 28/11/2008 and 03/12/2008 (Table 3.1).

Effects of Hyperfocal Distance on Target Appearance

When a camera and specific lens are focussed at the hyperfocal distance, any objects viewed from half this distance away from the camera to infinity will be reasonably in focus (Greenleaf 1950). By having an optics device focussed at the hyperfocal distance, it is likely that distant objects detected by the optical device will be in focus, and objects that appear blurry can have an estimated distance determined. This is useful in long-range nocturnal bird surveillance, where the focus is unlikely to be continuously adjusted. The hyperfocal distance is specific to a particular make and model of camera and the lens that is currently attached to it. This means that changing either to a different camera, or using a different lens on the same camera will change the hyperfocal distance.

To model the thermal imager (specifically the FLIR ThermaCam P60) as it is used during remote nocturnal surveillance, the focus was fixed at the hyperfocal distance for the 12° lens. Consequently, objects at half the hyperfocal distance to infinity away from a camera should appear in focus and clear. Objects closer to the camera will appear out of focus.

To calculate the hyperfocal distance, the camera's focal ratio (also known as f-number (N)) and circle of confusion size (c), along with the focal length of the lens (f) are required (Greenleaf 1950). This information was obtained for the FLIR ThermaCam P60 and associated 12° lens by contacting FLIR directly. The values were N = 1, c = 0.04625 mm, f = 72 mm. Hyperfocal length is determined using (Greenleaf 1950):

$$H \approx \frac{f^2}{Nc} \qquad \text{(Equation 3.1)}$$

Using (Equation 3.1), the hyperfocal distance was determined to be 112m. The thermal imager was set at 112 m away from the targets, and the surveyors focused the camera onto the targets. The equipment and target set up was identical to that used in Section 3.2.2 , Figure 3.2 and Table 3.2.

Starting from the 300 m point, the surveyors walked towards the target location. At each interval, the surveyors viewed the targets with the thermal imager and were asked to assess the quality of target appearance. As the focus was not adjusted, if the targets appeared out of focus, the surveyors were asked to describe how apparent this was on the targets. Details such as how 'soft' or 'fuzzy' target edges were requested from the surveyors.

Changing Target Layout

The layout of the targets was modified in response to the limitation encountered in 'detecting and identifying targets in known positions'. Prior to the field trial the order the targets would be installed at for each interval was determined. For the first 25 m interval all of the target orders were blind selected. For each proceeding interval three of the nine targets were selected at random and the positions for these targets were rotated from left to right (Table 3.2). For the trial, the rods were spaced approximately 80 cm apart. As the surveyors were unaware of which targets had switched, markers (the robust equipment cases as the observers said they could observe those easily) were placed between the 3rd and 4th rod, and the 6th and 7th rod. The purpose of the markers was to aid in determining which targets could not be detected.

	Position Number								
Distance from targets (m)	1	2	3	4	5	6	7	8	9
25	**LL**	MD	SM	**SL**	MM	LM	**ML**	LD	SD
50	LM	MD	SM	**SL**	**LL**	MM	**ML**	LD	SD
75	LM	MD	**ML**	**SL**	SM	MM	**LL**	LD	SD
100	LD	MD	**ML**	**SL**	SM	LM	**LL**	MM	SD
125	SD	MD	**ML**	LD	SM	LM	**LL**	MM	**SL**
150	SD	SM	**ML**	MD	LD	LM	**LL**	MM	**SL**
175	SD	SM	**ML**	LM	MD	LD	**LL**	MM	**SL**
200	SD	SM	MD	**ML**	LM	LD	**LL**	MM	**SL**
225	**LL**	SD	MD	**ML**	LM	LD	SM	MM	**SL**
250	**LL**	SD	MD	**SL**	LM	LD	SM	**ML**	MM
275	**LL**	SM	SD	**SL**	LM	LD	MD	**ML**	MM
300	**LL**	SM	SD	**SL**	ML	LM	MD	LD	MM

Table 3.2 Target layout over distance intervals. First character is size (S, M, L). Second character is shade (L, M, D). Grey highlights the targets that have been switched around at specific interval. Bold highlights the heated targets

3.2.3 Results of Field trials

Effects of Surveyor Bias

An attempt to understand how possible surveyor bias may affect target detection and identification rates, based on the targets being in a known order and shuffled was made. It was felt that the sample was too small for statistical comparison due to the low number of observers. A brief qualitative comparison was made by comparing which targets were detected and identified from both approaches. Interestingly, RW detected more shuffled targets whilst NG detected more targets when they were in order. This initially suggests that in this instance the order of the targets may not greatly affect surveyor bias.

Effects of Target Shading on Detection and Identification on Image Intensifier

All targets with the same shade were grouped together as size variance was constant. Mean surveyor values from the completed full moon field trials and new moon field trials were used. Target detections have been separated over full moon and new moon nights and are presented in Figure 3.6 and Figure 3.7 as percentage detections. Target detection/identification is defined as whether a target is detected/identified at a certain distance interval. So, if the same target is detected at 25 m and at 50 m, these are treated as two detections.

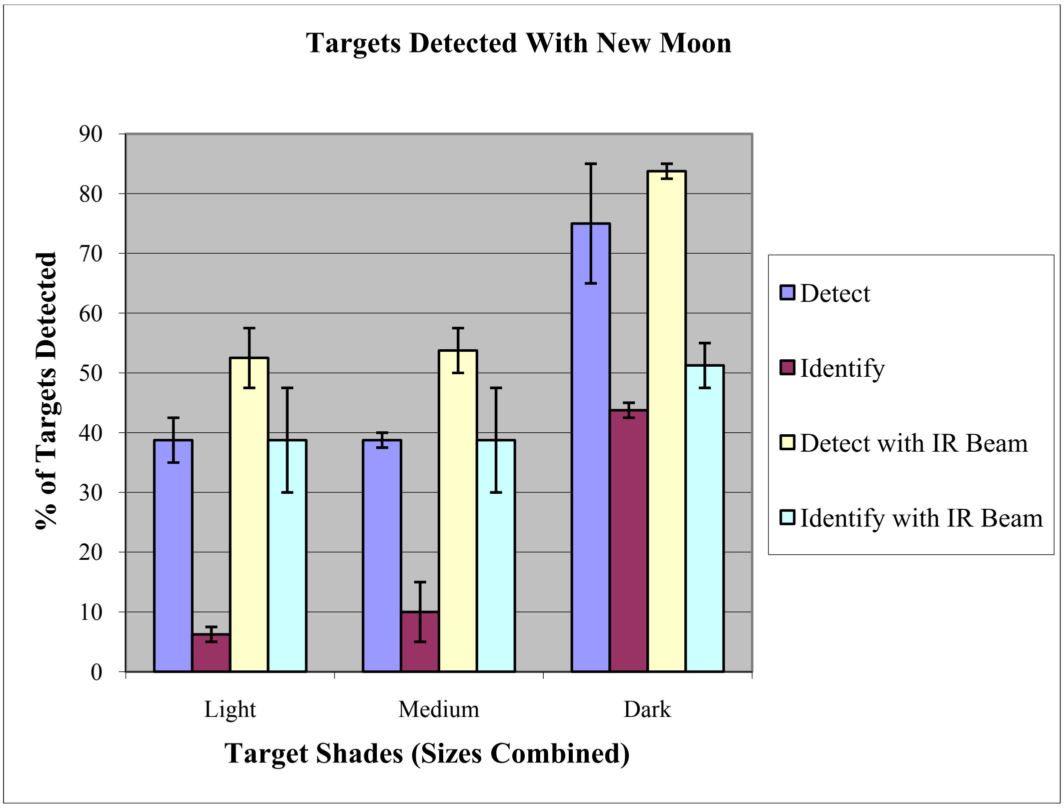


Figure 3.6 Effects of target shading on detection and identification rates during new/near new moon nights. IR beam = infrared light beam. n = 2

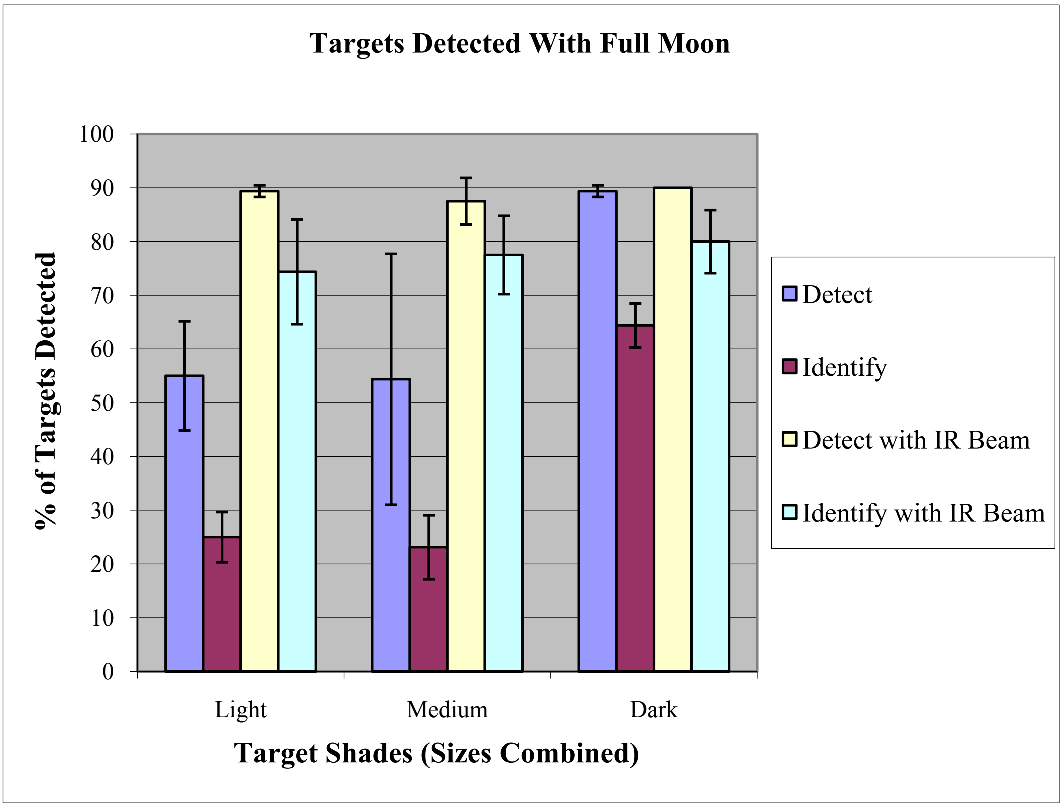


Figure 3.7 Effects of target shading on detection and identification rates during full/near full moon nights. IR beam = infrared light beam. n = 4

Equipment Comparison

To compare the night vision equipment, all target detections and identifications (size and shading) were grouped together for new and full moon, using mean surveyor values, represented as percentage values in Figure 3.8. As the thermal imager is not dependent on light, the differences in target detection and identification is attributed to the use of the old heating system during the full moon evenings and the new heating system during the new moon evenings.

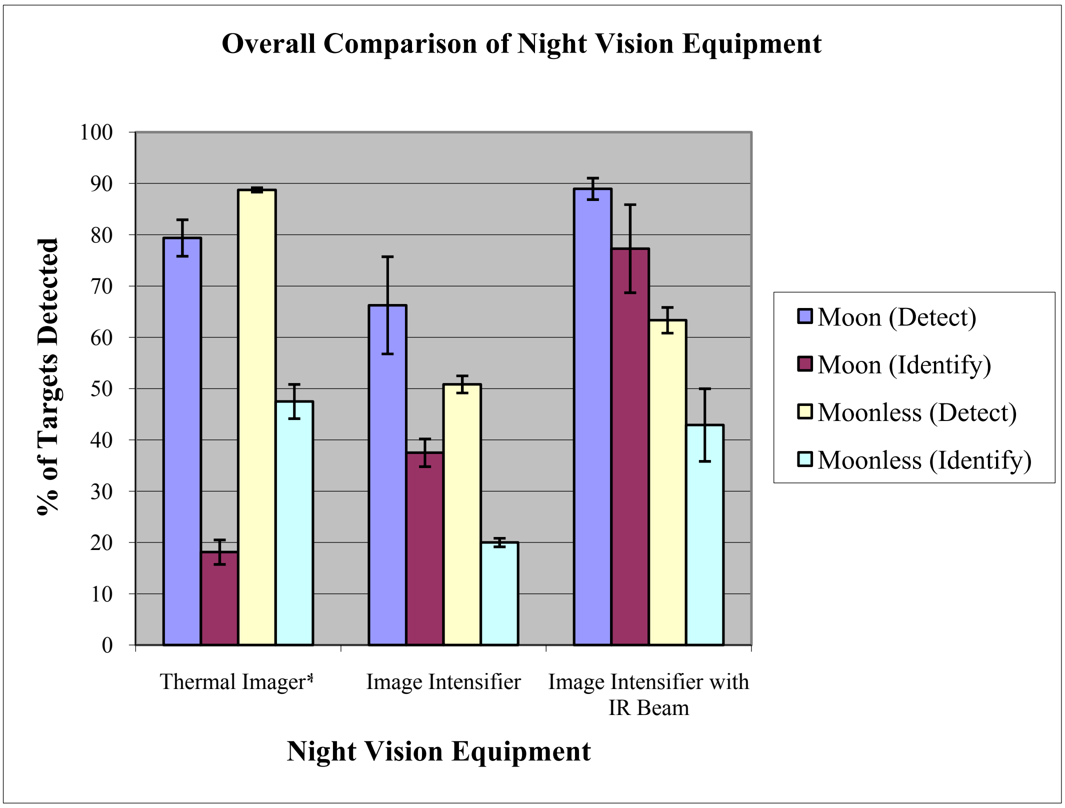


Figure 3.8 Overall comparison of the thermal imager, image intensifier and image intensifier with infrared beam for detecting targets in full moon (n = 4) and new moon (n=2) nights

The following two tables provide a guide for the maximum detection and identification distances for the thermal imager and image intensifier based on the targets. Table 3.3 provides the distances for the thermal imager. Only sizes are provided as the thermal imager is light independent. Table 3.4 provides the distances for the image intensifier based on target shading and size during full moon and moonless nights.

Target Size	Small	Medium	Large
Maximum Detection (metres)	300+	300+	300+
Maximum Identification (metres)	150	200	225

Table 3.3 Maximum detection and identification distances for thermal imager based on target size

	Distance (m)	Light			Medium			Dark		
		Small	Med.	Large	Small	Med.	Large	Small	Med.	Large
Full Moon	II Detect	225	250	250	200	300+	300+	300+	300+	300+
	II Identify	100	125	175	50	100	175	150	250	300+
	IR Detect	300+	300+	300+	300+	300+	300+	300+	300+	300+
	IR Identify	300+	300+	300+	300+	300+	300+	300+	300+	300+
New Moon	II Detect	75	175	175	50	175	175	250	300+	300+
	II Identify	25	25	25	25	25	125	125	175	175
	IR Detect	175	200	200	175	200	200	250	300+	300+
	IR Identify	125	175	175	125	175	175	175	175	200

Table 3.4 Maximum detection and identification distances for image intensifier during new moon and full moon field trial nights. II = image intensifier, IR = image intensifier with infrared lamp

Appearance of Targets at Fixed Focus

Two of the surveyors reported that the heated targets had the appearance of 'softness' around the edges at 75 m away from the targets with the thermal imager set at the hyper focal distance. At 25 m, the targets appeared even softer, and less clear. The other two surveyors felt that the targets were reasonably in focus at 25 and 50 m away from the targets.

3.2.4 Discussion of Field Trial

The darker-shaded targets had a higher detection rate than the lighter-shaded targets. The surveyors remarked that the dark-shaded targets produced a greater contrast against the hedgerow background, making them easier to detect and identify.

During full moon, target shading appears to have little effect on detection and identification rates using the image intensifier with the infrared lamp. During new moon, there was an effect, with the dark-shaded targets having a higher detection rate. Overall, the ambient light from a full moon has an observable effect on target detection and identification rates on the image intensifier, both with and without the infrared lamp.

The infrared lamp made a comparatively large difference in detection and identification of the targets overall compared to the image intensifier alone. Overall comparison of all of the equipment suggests that the thermal imager can detect a far larger number of (heated) targets compared to the image intensifier. As all birds emit body heat, it is expected that more birds would be detected using the thermal imager compared to the image intensifier. The image intensifier did however identify more targets overall compared to the thermal imager, when accompanied with the infrared lamp. Where similarly shaped, different species birds are present, such as intertidal studies, accurate target detection is important. For areas where there are a limited number of bird species using an area, target detection and shape may be adequate for bird identification.

There is a noticeable difference between the identification rates between the thermal imager on a full moon night and a new moon night. This is due to the changes to the heating systems to the medium and large-sized targets to make them more representative of bird targets. Hence the thermal imager results from the full moon trials are considered to be invalid and not representative of the thermal imager.

Looking at maximum distances each target was last detected and identified at (Table 3.3 and Table 3.4), detection and identification range of a heated target for a thermal imager appears to be related to target size. Detection and identification range of a target using an image intensifier (with or without the infrared lamp) depends on shading as well as target size.

It was unclear on how focusing the thermal imager at its hyper focal distance affected the appearance of the heated targets at the 25 and 50 m intervals. Surveyor feedback on the apparent softness of the targets conflicted.

3.2.5 Conclusion of Field Trial

Overall, based on the field trials, no benefit can be identified in using the image intensifier without the infrared lamp for nocturnal bird surveillance. The thermal imager produces higher target detection rates as compared with the image intensifier alone. The image intensifier (coupled with infrared lamp) produces higher target identification rates compared to the thermal imager.

The surveyors unanimously agreed that the difference in target-background contrast, rather than the shade, affected how easily they could see a target (using the image intensifier). Hence, it is felt that less emphasis should be placed on a particular shade of a target (e.g. Allison and DeStefano 2006), but more on the contrast difference between a target and the background that surrounds it. This becomes relevant if a distant bird target's plumage and the background that surrounds it are similar, possibly causing a surveyor to miss it.

An issue to be wary of is the high identification rates suggested by the thermal imager. Whilst shape can be determined through the thermal imager, plumage and feather shading of a bird could not. Hence whilst bird species identification down to bird families (e.g. ducks and geese) is possible based on bird shape, it may not be possible to identify individual species or allied species groups without further identification cues including fine detail of plumage pattern, bill and leg length and behaviour.

There was a noticeable change in thermal imager identification rates when the new medium and large heated targets were used for the field trials. The surveyors commented that the new heating systems for the medium and large targets represented bird heat profiles more accurately.

The field trials and interviews were conducted using RPS staff only. This may bring a limitation as company-focussed objectives may have produced subjective results. One of the field workers (RW) had extensive field experience of image intensifiers prior to joining RPS. Also others involved in nocturnal bird monitoring such as those based at the British Trust for Ornithology have also reported similar experiences. Some of the findings from the interviews and the field trials also show some correlation with published literature in the field, as outlined in Chapter 2.

Due to the limitations of only conducting surveys during or very near full and new moon nights, during periods of acceptable, consistent weather, and availability of trained staff, only four nights were available to gather data. Ideally, more nights would have been used, however the data gathered was fixed within the described constraints.

The field trial presented in this section only deals with targets against a background. It is limited in that it does not compare the equipment when looking at birds flying against the sky. In these conditions, the equipment may perform in a different way. It is recommended that an aerial trial is carried out.

3.3 The Effects of Fog on Image Intensifier and Thermal Imager

3.3.1 Introduction

Fog occurred during the field trial on 28/11/2008. As all the targets were set out at random, the opportunity was taken to explore further the effects of fog on the use of a thermal imager and image intensifier with and without an infrared lamp. This extends to some degree the work that Desholm (2003) did to determine target detection rates for a thermal imager in fog. Desholm used a caged pheasant to assess the detection range of a thermal imager during light fog (visibility 200 m) and heavy fog (visibility 30 m) using a 12° lens. The caged bird was moved away from the thermal imager at 25 m intervals, and images taken to review how the bird appeared at each interval. This study found that in heavy fog the pheasant could not be seen at distances beyond 70 m. In light fog, the pheasant could be seen at least 175 m away from the camera. The thermal imager used by Desholm in this study is very similar to the imager used in these trials, and the camera magnification is identical.

When the fog occurred, the surveyors estimated visibility to be 50-100 m, on a new moon night. This estimate was based on buildings and other objects that could be seen in the fog.

3.3.2 Method for Assessing the Effects of Fog on Image Intensifier and Thermal Imager

As in the previous section, rods were spaced out 80 cm apart, the targets were laid out in order relating to 150 m interval in Table 3.2. At 150 m the surveyors reported that they could not see the targets using the image intensifier with or without the infrared lamp. For the intervals from 175 m to 300 m, the surveyors described which targets they could see and identify. Returning to the 175 m interval, the surveyors used both the thermal imager and the image intensifier (with and without infrared lamp) to determine which targets could be detected and identified.

3.3.3 Results for Assessing the Effects of Fog on Image Intensifier and Thermal Imager

The numbers of target detections for each piece of equipment were grouped together (mean observer sightings) and then compared against those from a clear, near new-moon night. This is presented in Figure 3.9.

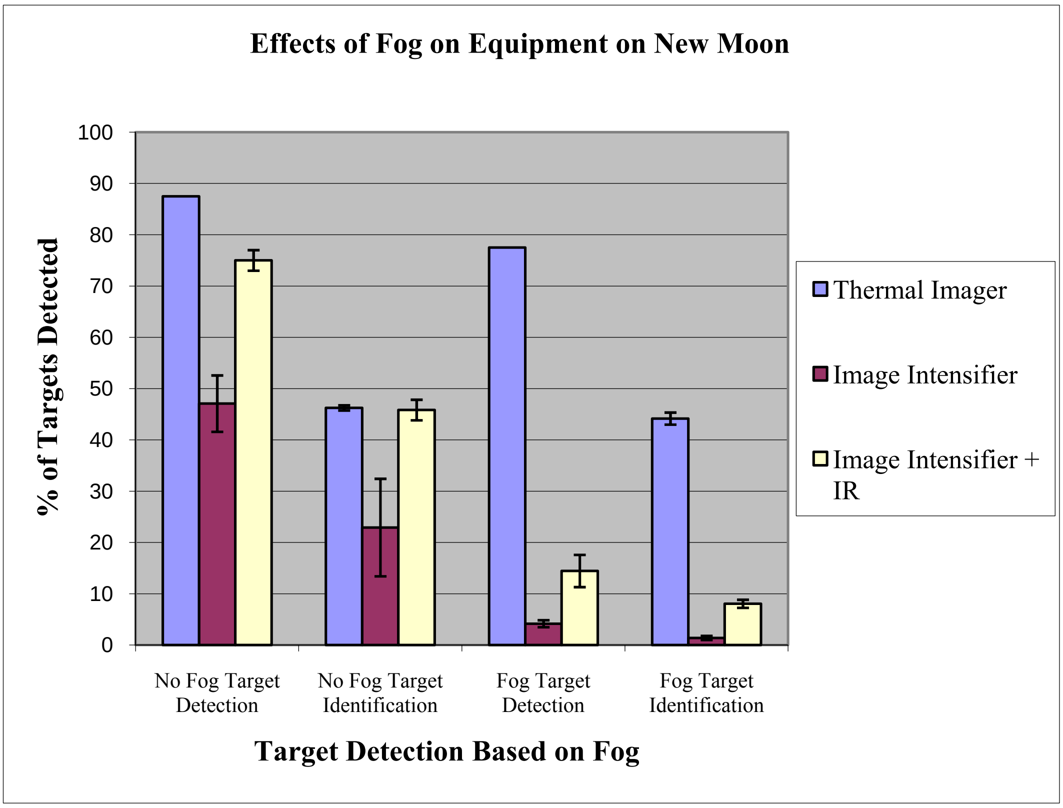


Figure 3.9 Comparison of equipment detection and identification rates on a new-moon night, with (n = 3) and without fog (n = 2). IR = infrared lamp

To get an overview of how target size and shading affected detection and identification rates, the maximum distances are presented in Table 3.5.

Maximum Distances (m)	Targets (Size – Shade) Light			Medium			Dark		
	Small	Med.	Large	Small	Med.	Large	Small	Med.	Large
II Detected	X	50	25	X	X	25	X	75	75
II Identified	X	25	25	X	X	25	X	25	25
II+IR Detected	25	50	75	50	75	75	50	75	75
II+IR Identified	25	25	50	25	50	25	25	25	25
TI Detected	175	300+	300+	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
TI Identified	150	150	150	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*

Table 3.5 Maximum distances each target could be seen during the fog. II = image intensifier, IR = infrared lamp, TI = thermal imager. 300+ = targets were detected at 300

m, but may have been detected further away. X = not detected/identified at all. Only the light-shaded targets were heated for the thermal imager

During the trial, the surveyors commented on difficulties they found with using the infrared lamp in the fog. They reported that the lamp reflected off the fog water droplets, causing glare and reducing visibility.

3.3.4 Discussion of the Effects of Fog on Image Intensifier and Thermal Imager

The detection and identification rate of the image intensifier was greatly affected by the fog. The infrared lamp provided little improvement, extending target detection to no more than 75 m. At 75 m, the surveyors could only detect eye shine (reflected by the infrared lamp), and could not make out target shape.

The fog also affected the thermal imager, but to a lesser extent relative to the image intensifier. The medium and large targets were still detectable at the 300 m interval, although identification for all three targets was limited to 150 m.

3.3.5 Conclusion for Assessing the Effects of Fog on Image Intensifier and Thermal Imager

The Study carried out in fog provided a more practical understanding of its affect on the detection and identification ranges on the thermal imager and image intensifier. This extends the work done by Desholm (2003), by including size information as well as effectiveness of the image intensifier.

The thermal imager performed well in the fog, detecting and identifying targets beyond the 50-100 m of visibility. The medium and large targets could be detected beyond 300 m. The image intensifier was severely affected, failing to detect targets beyond the 50-100 m of visibility. The infrared lamp provided no additional assistance.

This trial has highlighted how limited survey information is from an image intensifier during adverse conditions. Surveys using an image intensifier during fog must be repeated in more favourable weather. An area perpetually affected by fog that requires monitoring should consider using a thermal imager for surveillance.

3.4 User Attitudes to Nocturnal Surveys

3.4.1 Introduction

Although the field trials offer valuable insights into the advantages and limitations associated with thermal imagers and image intensifiers, and provide an understanding of how they compare side-by-side, there are a number of field scenarios that are difficult to model. For example, the available background during a field trial may not be uniform; birds may be airborne and flying against a dark sky, or on the ground, feeding in a cropped field. Surveyor experience has the potential to provide further insight into each piece of equipment.

During the life of this research project (2005–2008), ornithologists based within RPS have gained much experience using both a thermal imaging camera and an image intensifier (FLIR ThermaCam P60 and Thales Maxi Binokite respectively) on a number of nocturnal bird surveys, accumulating hundreds of hours of experience with the equipment. The purpose of this section is to benefit from their knowledge and experience, and to integrate this information with that gained from the field trials. In addition to specific equipment advantages and limitations, the surveyors were aware of environmental conditions that could impact upon nocturnal bird surveillance.

The image intensifier and thermal imager were used in specific surveillance styles for RPS surveys. The image intensifier was used as a portable viewing device which was freely panned at different heights and altitudes. The surveyor would move to different vantage points and scan the area for bird activity. The thermal imager was used primarily for static point surveillance. Connected to a laptop to store the imager's output as video, the thermal imager would monitor fixed airspace. Once the survey is concluded motion detection software was used to remove periods of inactivity from the stored video. These are experimental approaches and the thermal imager could be freely panned to survey an area.

Likewise an image intensifier (if it has a suitable video output socket) could be used for static surveillance.

In order to benefit from this experience, three RPS ornithologists were interviewed about their use of the equipment. The aim of this study was to seek the interviewee's opinions on the strengths and weaknesses of thermal imagers and image intensifiers. This was done by exploring the past nocturnal surveillance projects the surveyors had been involved with, and extrapolating what factors, such as surveillance information, landscape, weather and aims of survey affected the night vision equipment.

3.4.2 Methodology for User Attitudes to Nocturnal Surveys

Semi-structured one-to-one interviews were selected as a method for obtaining user experiences on nocturnal bird surveys. This form of investigation was selected as the number of candidates available was low, and interviews offer the opportunity for greater detail and individual interviewee opinion rather than through a single focus group (Burningham and Thrush 2004). Also, semi-structured interviews are flexible and different lines of questions can be used (Young and Stanton 1999).

A total of three surveyors were interviewed. These surveyors were from the RPS Ecology Survey Unit (ESU) and carried out the majority of nocturnal bird surveillance for RPS. As with the previous section, there were a limited number of personnel that had experience in using night vision equipment for bird surveys within the organisation, hence the small sample size. As the number of ornithologists who carry out nocturnal bird surveillance using night vision equipment increases, further interviews on their experiences could be pursued.

Although the ESU are highly skilled ornithologists, there was some variation in the experience each of the interviewees had with the two pieces of night vision equipment (Table 3.6). One of the interviewees only had experience with the image intensifier with some interaction with the thermal imaging camera, whilst the other two interviewees had experience with both the image intensifier and the thermal imaging camera over a number of surveys (Table 3.6). All three of the interviewees have multiple nocturnal survey experience with a night vision tool.

Prior to commencing the interviews with the ornithological surveyors, the purpose of the interview was explained to each interviewee. Interviewees agreed to answer additional questions should they arise subsequent to the interview. Interviews took place in a dedicated meeting room. All interviewees were asked to provide details of their nocturnal survey involvement, along with their knowledge on other existing nocturnal surveillance techniques they were aware of, but had not necessarily used. Information on the sites where surveys took place, such as landscape, lighting and weather was gathered, along with survey protocol, goals of the survey and feedback on the equipment. Further information was gathered based on the user's opinion on the strengths and weaknesses of the equipment in different surveillance scenarios. Reflecting on this experience, the interviewees were asked their opinions on how the equipment could be used more effectively on future nocturnal bird surveillance tasks.

Other questions were raised during the interviews to explore further experience and thoughts on equipment and survey, site and weather conditions and opinions with further probing questions to obtain additional details where relevant.

The transcripts collected during the interviews are located in Appendix D.

3.4.3 Results of User Attitudes to Nocturnal Surveys

As outlined in Table 3.6 the surveyors have gathered much experience from different survey locations, using the equipment to monitor different target species with differing surveillance aims.

Detecting bird targets was considered to be easier using the thermal imager than the image intensifier, especially in situations that would challenge the image intensifier, such as in very dark conditions, ploughed fields (especially without the infrared lamp) or targets flying against the sky. The thermal imager worked best at detecting objects that otherwise would not be seen with an image intensifier, such as “geese and other large species migrating at distance” from the camera, and “good for confirmed Golden Plover over a considerable range” (RM). The thermal imager has a better detection rate compared to the image intensifier. RM commented that “the thermal imager excels where identification is not important, such as when you have prior knowledge what is present” and “if trying to locate animals in [a] cryptic environment, such as a ploughed field, the thermal imager is good because it detects heat”. AS commented on the thermal imager: “[it is] able to pick up stuff in the sky in the dark, especially when it is really dark – may be difficult to pick up something in the sky with nightsight [image intensifier] – easy with thermal imager”. Although target detection was considered to be straightforward, target identification was felt to be much harder. The surveyor commonly relied on the speed of an object passing the cameras field of view and the flight style to identify the target, with little or no shape information available to aid the surveyor. Larger targets, such as ducks, geese and waders were easier to identify “to family or group, not to species without additional information” (RM). With smaller objects at distance, such as passerines “[it was] not possible to identify without additional information” (RM). There was also concern with confusing, or struggling to differentiate small bird targets from bats and possibly insects.

RPS Project Name	Location	Site Description	Surveillance Aims	Metho
Abberton	Essex	Large reservoir. Areas of light pollution	Distribution and activity of wildfowl over a large reservoir	Reservoir counts an descriptions of wild
Alaska	Dorset	Heath land, rolling hills	Determine Nightjar activity levels. Obtain Nightjar flight height information	Variable height van survey. Sampling su
Besborough	South West London	Two small reservoirs, illumination from street lights	Distribution of wildfowl for two winter periods	Reservoir counts of
Bleak House	Staffordshire	Arable farmland, undulating land. Some light pollution	Nightjar presence/absence	Vantage point surve Sampling survey
Carscreugh	Lanarkshire	Southern uplands	Golden Plover presence/absence	Vantage point surve
Coventry Farm	Cambridgeshire	Arable farmland. A14 and A10 passing by site.	Establish knowledge on Golden Plover activity	Scoping survey Sampling survey
Lanarkshire	Lanarkshire	Southern uplands	Pink-footed Goose presence/absence	Vantage point surve
Tilbury Foreshore Surveys	Tilbury	Shorelines by power station. Some light pollution.	Distribution of waterbirds at high and low tides	Shoreline counts of waders
South West London	South West London	Reservoirs	Distribution and activity of wildfowl	Waterbody counts a descriptions of wate
Stonish Hill	Nottinghamshire	Woodland with areas of pasture	Nightjar presence/absence	Vantage point surve Sampling survey

Table 3.6 Summary of surveyor involvement in nocturnal surveys, survey aims and method used. II = image intensifier, II + I thermal imager

Optimum Operating Conditions for the Image Intensifier

From the interviews, the main factors that provided optimal operating conditions for the image intensifier were the use of an infrared lamp, other ambient lighting available, the 'backdrop' for the image intensifier and the nature of the weather. Use of the infrared lamp had a significant impact on how well the image intensifier operated. Without the lamp, images were grainy. The infrared lamp greatly increased the distances that targets on the ground could be detected, from 100-150 m without the lamp to 300-400 m with the lamp. The infrared lamp was also beneficial in detecting targets by generating eye-shine to be spotted with the image intensifier. The moon, and to some extent, light pollution, play a big part in how well the image intensifier operates. A "decent size moon, half to full" (AS) provides optimal illumination for the image intensifier. A cloudy night negates any benefit from ambient lighting provided by the moon. The most favourable time in the day for the image intensifier is "2-3 hours after sunset and 2-3 hours before sunrise when there is some light" (AS). Light pollution could either help or hinder the image intensifier. Some situations, such as work at Tilbury (foreshore surveys (Table 3.6)) had "areas with light [meant that the surveyor with the image intensifier] picked up most birds up to 200-300 m [away]". AS reported that "lights in behind of the nightsight [image intensifier] provided additional ambient lighting which helped in the field". However "lights in front of the nightsight impedes seeing objects. Looking at water with lights close by made it difficult to use the nightsight" reported AS working at the Besborough site (Table 3.6). The suggested resolution by AS was to "change the angle at which the area is being observed so that [the] lights run perpendicular to the area being scanned". Overall, some form of lighting, whether artificial, celestial or from the infrared lamp was considered necessary to use the image intensifier. "Pitch black are the worst conditions" (AS) for using the image intensifier.

The background scene viewed through the image intensifier also affects how well targets are detected. The surveyors found it easier to detect targets on the ground. It "may be difficult to pick up something in the sky with the nightsight [image intensifier]" (AS). Looking against the sky, the infrared lamp failed to improve target detection, with the target detection range dropping off to 50 m. Against the ground, "dark backgrounds, such as a ploughed field make it very hard to see" (RM) with an image intensifier. Ideally, a "crop 0-7 inches high" (AB) was ideal for detecting and identifying targets on the ground. Crops higher than this made it difficult to see targets on the ground. The "best situation is when the land is sloping down away from the surveyor" (AB). Other backgrounds, such as tall grass, wet mud, open fields (preferable to woodland) and skyline improved target detection.

Ideally, the image intensifier should be used in dry conditions. Drizzle and rain impede the operation of the image intensifier. The drizzle affects the image intensifier by "putting a fine haze across it" and "appears to shut out light" (AS). In rain, surveys sometimes had to be abandoned, e.g. rain droplets on the lens can have a magnifying effect. In misty conditions (visibility of 50 m), the surveyor "can see very little" (RM). Also, windy conditions may make it more difficult to identify birds due to changing their shape, and "shake on the image intensifier makes it impossible to use, even with a tripod" (AB). Temperature can have an adverse affect, with the lens steaming up as temperatures approach $0^{o}C$, from the breath and body heat from the observer on the eye-piece.

Optimum Operating Conditions for the Thermal Imager

Lighting conditions do not affect the thermal imager, unlike the image intensifier. Not much information was available on how the thermal imager performed in precipitation, as it would be turned off during rain. Hence overall the interviewees did not have as many comments to make on the thermal imager compared to the image intensifier. As the thermal imager detects heat, looking at the sky it is easier to detect targets with the thermal imager compared to the image intensifier. Land in the camera field of view "helps give perspective of distance", where as "too much background clutter can make it difficult to identify targets" (AS). Another consideration is based on how the thermal imager is set up. On adjusting the colours to represent temperature ranges it is important in "getting the colours and range right to detect stuff. Colours used [during the Bleak House project were] possibly too bright to see detected targets" (AS). The surveyors also commented that there was no depth perception, making it difficult to visually differentiate between near and far objects without further information, such as background cues, hampering visual approximations of target distance. Also using the equipment is not intuitive as compared to the image intensifier.

Surveys using either the image intensifier or thermal imager may cease during poor weather. Poorer weather may also lessen the likelihood of detecting certain species if they are less active during these periods.

Equipment Ranges

Based on the experiences of the three surveyors, a good indication can be provided of the distances/ranges over which the two pieces of equipment are most effective and under what conditions. The optimal operating conditions (Table 3.7) identify the ranges reported by the surveyors for the image intensifier and thermal imager in ideal survey conditions (weather and illumination as outlined above). Other conditions describe observed target detection ranges based on other factors encountered by surveyors (Table 3.8). The detection and identification ranges listed in the tables are either the common stated values, or minimum-maximum values reported by the interviewees.

Equipment	**Range (m)**	**Comment**
Image intensifier with infrared lamp	300-400	Looking towards ground, down slope, and identify target
	200	Most other situations, and identify target
	50-100	Looking against clear sky. Infrared lamp makes little difference, and identify target
Thermal Imager	300-400	Target detection range
	150-200	Target identification range (some targets such as passerines and waders could not be identified as close as this – RM)

Table 3.7 Estimate ranges for equipment under optimal conditions

Effect	Range (m)	Comment
Light pollution behind image intensifier	200-400	No infrared lamp used
Light pollution in front of image intensifier	70	No infrared lamp used
Rain	50-100	Appears to shut out light and water droplets on lens cause spot magnification. Infrared lamp makes less of a difference than in optimal conditions
No Moon	50 200-400	No infrared lamp With infrared lamp
Full Moon	100-200	No infrared lamp
Thermal Imager (Optimal Conditions)	300-400 150-200	Target detection range Target identification range (some targets such as passerines and waders could not be identified as close as this – RM)

Table 3.8 Estimate of ranges for image intensifier in other conditions to identify target. Thermal imager ranges from Table 3.7 included for completeness

There have been one-off exceptions where the range has been far larger with the image intensifier. Two examples (given by AB) were identifying an Eared Owl (unsure whether Long-Eared or Short-Eared) 1-1.5 km away and Wood Pigeon identified 600 m away by chance and a Barn Owl aided by illumination from lorry's headlights. In addition in past projects using the thermal imager geese have been detected over 1 km away against the sky and roosting. It is important to note that the ranges provided here are mainly dependent on the magnification of the lens used. However, the magnification of the image intensifier (x6) and the thermal imager (x2) are considered to be commonly encountered in similar nocturnal surveillance work.

Other Factors Affecting Equipment Operation

The strengths and weaknesses covered in the above sub-sections are environmentally dependent. Other factors that affect equipment operation described by the interviewees are provided below.

For the image intensifier, the following additional advantages were described by the interviewees. The image intensifier "can be used as binoculars are during the day … as you can sweep around you feel as though you will pick up more targets"

(RM), providing a large viewshed. This can quickly assess large areas for bird activity, providing a 180° sweep. Also the image intensifier is "portable" and "simple to use" (RM). There are, however, disadvantages associated with the image intensifier. As the image intensifier is being used to scan an area there is a concern that a surveyor "might miss birds as it is difficult to identify whether stuff is being missed" (AB). If a surveyor has not observed the presence of a bird target during nocturnal surveillance, they could not confidently say that particular species was not using the surveyed area. This is also applicable to the thermal imager. Another drawback is that a surveyor "can only use the image intensifier in 10 minutes in succession before passing the image intensifier to a colleague" (AB). The images produced by the image intensifier and the close proximity of the generated images to the surveyors eyes can cause discomfort with prolonged periods of use. It has been determined by RPS that a rest is needed after 10 minutes of image intensifier continual use. Therefore to get adequate surveillance sampling effort, additional surveyors may be required for the surveillance task, and take turns in using the image intensifier. If the thermal imager was used in the same was as the image intensifier, there would also be a limitation as to how long the screen could be viewed before there was evident discomfort on the surveyor's eyes. Due to the colourings of the video output from both devices and the differing appearance of targets, is it speculated that a surveyor could use a thermal imager for longer periods of time compared to the image intensifier in like for like surveillance.

Strengths and Limitations of Surveillance Approach

The two surveillance approaches used with the equipment, scanning and panning verses monitoring a fixed point have their associated advantages and disadvantages. Continuously storing video allows the data to be retrieved later reducing the likelihood of missing targets. The associated motion detection software was also seen as an advantage, especially "where you have to monitor a specific location remotely" (RM). Using the associated system for storing video, effort can be concentrated on a particular part of airspace and "not relying on humans to keep concentration" (AS). Using the associated peripherals (laptop to store surveillance video and motion detection software to remove video of inactivity), "gives some way of monitoring a certain height with respect to environmental statements" (RM). As the angle of the imager is known when it is set up to survey a location, any detected targets can have their flight heights approximated, based on trigonometry. Another disadvantage with using a fixed surveillance point was the narrow field of view. RM commented that the "you may have a situation of a turbine airspace sample for 180° sweep ... versus field of view sample of turbine". With a surveyor continuously panning, the airspace of several wind turbines could be under surveillance. With an imager set up at a fixed point, it would only be able to continuously monitor a section of individual wind turbine airspace, as it is not panning, and the field of view on the imager is relatively narrow with high magnification. This approach alone may not be adequate for determining the presence or absence of bird species at a site. "[There are] limitations on statements that can be made" (RM). A fixed surveillance point works better at monitoring specific areas for activity, with panning and scanning used to back up presence/absence and numbers, reducing the limitations of using a fixed point alone.

The whole recording system associated with the thermal imager for static point monitoring was also considered to be quite heavy to move around, extending survey time, but was not considered to be that big an issue.

Choosing Equipment and Approach for Nocturnal Surveillance

Overall, there appeared to be a consensus for which piece of equipment would be the most suitable for a given survey. Assuming favourable conditions for surveys that involved scoping an area for bird activity and identifying bird species the image intensifier would be the best choice as it could provide a rapid assessment of numbers and was portable. As described by RM, the image intensifier "can be used like binoculars" and "can give reasonably accurate assessment". Also there is a "direct interpretation of a scene with an infrared lamp. You can get a very good assessment at night" (RM). The thermal imager was superior at detecting bird targets, especially against the sky and is not affected by light levels.

Using fixed-point surveillance and storing the video was seen as a good tool for specific airspace monitoring. RM commented that this approach (thermal imager used) was ideal where continuous quantities of data would be collected, and expecting a human observer to observe it uninterrupted would be impractical. With the video being stored, the system could be left to gather data, the software detection facility to remove video of inactivity, and removes the need for persistent surveyor concentration. Both surveillance approaches can be combined to generate quantitative data for collision risk and height information from fixed-point surveillance, whilst scanning supplements the collected data. As the thermal imager is far more effective at detecting targets (although not necessarily identifying them), is completely light independent and can directed at the sky, it is more suited to be used for fixed-point surveillance than the image intensifier.

3.4.4 Discussion of User Attitudes

The interviews were primarily concerned with finding out the advantages and limitations of the night vision equipment used on a number of surveys. Effects such as natural and artificial lighting, landscape and weather were explored. In addition to assessing strengths and weaknesses of the equipment, the thought processes in survey planning were also investigated. As the surveyors participated in more nocturnal ornithological surveillance projects, experience from previous projects was used to feed into new ones. Nocturnal surveying of bird activity is a relatively new field, and there is much experience being gained.

3.4.5 Conclusion of Survey of User Attitudes to Nocturnal Surveys

The interviews confirmed that neither piece of equipment was superior to the other, with either the image intensifier or the thermal imager having its place depending on the aims and variables associated with a particular nocturnal survey. In certain situations, there was value in having both pieces of equipment working together.

The interviews have revealed a number of key points future organisers of nocturnal surveys should be aware of and consider when planning the next survey. These include:

- the purpose of the survey: Is it a scoping survey? Are vantage points being used? Is there a need for focussed effort?
- likely weather conditions, e.g., areas susceptible to fog may rule out a type of night vision implement or the survey altogether;
- area and species under surveillance: Is airspace being monitored? Is bird behaviour at ground level of most interest? Is it known what the species is likely to be?
- detections versus identification: What is more important from the survey? To assess numbers of non-specific species, or to identify the species using a site?

The interviewees have gained much experience and insight into how to approach nocturnal surveillance tasks, and this is witnessed through the adaptation and improvement of subsequent nocturnal bird surveillance. This is an iterative process and feedback from further experiences and from other surveyors will be valuable in helping to further develop these methodologies.

3.5 Discussion

From the field trials and supported by the interviews, the image intensifier operates considerably better when accompanied by an infrared lamp to provide additional illumination. From the field trials, the ambient lighting the moon provides has a prominent effect on target detection and identification rates when the image intensifier is used. Target shading also affects detection rates. This is less relevant when an infrared lamp is being used, supported by adequate moonlight. The behaviour of some species, such as Golden Plover, has been observed to be influenced by the moon (e.g. Gillings *et al.* 2005). Using an image intensifier only during optimal conditions (i.e. during full moon) could bias any surveillance results.

The thermal imager is good at detecting targets. This was highlighted in both the field trials and in the interviews. However, it is lacking when it comes to target identification, compared to the image intensifier.

The incidental fog had an impact on the image intensifier in both detection and identification rates. The fog appeared to have less of an impact on the thermal imager, although distances at which target shapes could be observed reduced. The interviews also support that poor weather affects visual nocturnal surveys, and may result in poor value data.

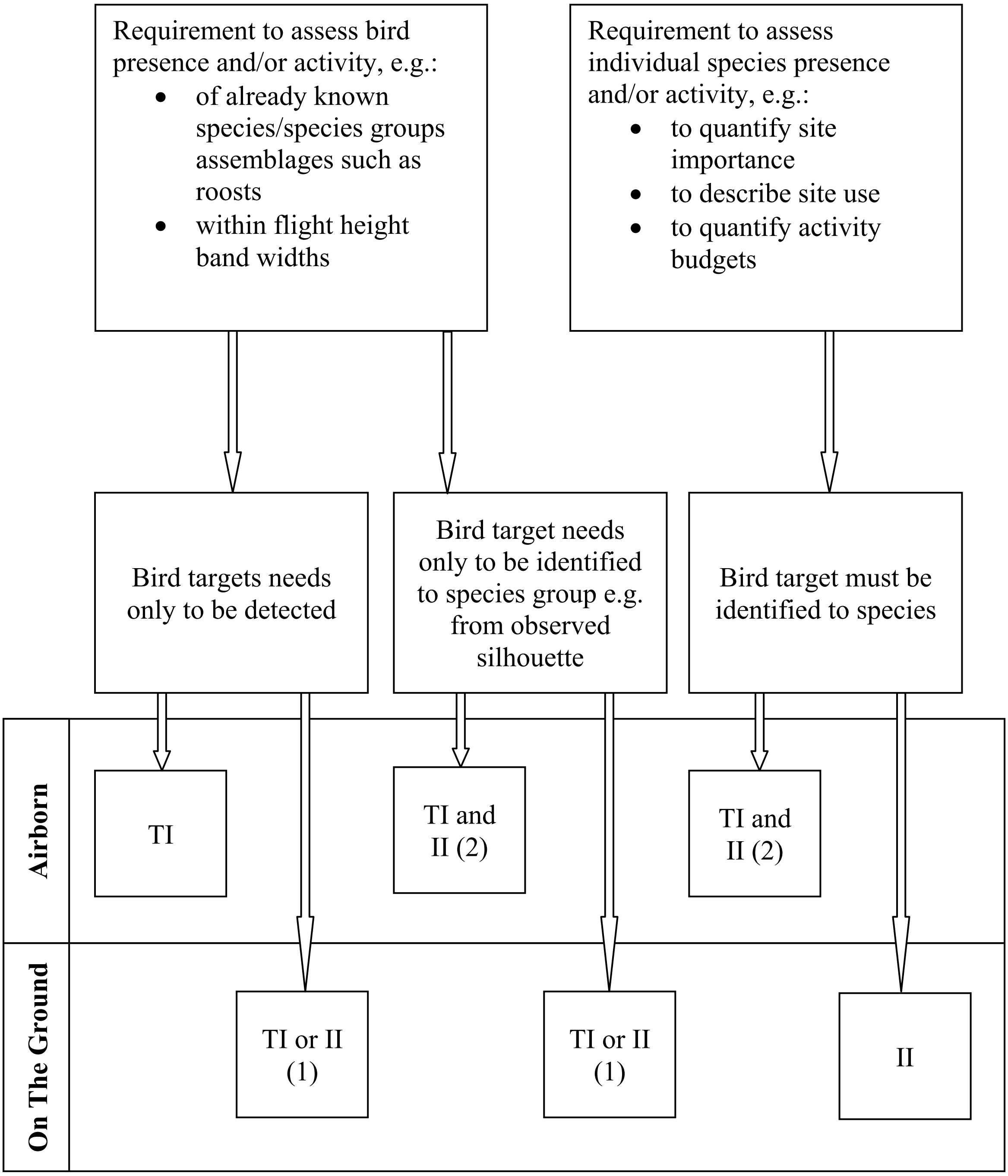
From the interviews, the image intensifier, when accompanied with an infrared lamp, is best placed as a tool for scoping a site for bird species presence/absence, understanding bird activity and establishing numbers. If a specific area, such as airspace needs to be monitored, or an area requires large periods of survey effort, the thermal imager would be a more appropriate choice. Both the image intensifier and the thermal imager can be used in conjunction to deliver multiple aims for a nocturnal survey, such as assessing species numbers and sampling flight heights near at-risk altitudes. Table 3.9 provides a summary of thermal imager and image intensifier attributes collated from the field trials and surveyor interviews. For a guide as to how the imaging equipment could be used in survey scenarios Figure 3.10 provides a flow diagram for situations where a thermal imager (TI) or image intensifier (II) may be used. It is likely that more than one of the instances presented in Figure 3.10 will be carried out during a nocturnal survey, so both the thermal imager and image intensifier may be combined to meet those aims. Although the guidance presented in Table 3.9 and Figure 3.10 will provide a sound approach for survey planning, it is recommended that the surveyor checks whether new techniques or updates on currently used methods have been made available. For work that specific bird species behavioural monitoring, it may also be worth considering how radio tracking may aid the survey in addition to the use of night vision equipment.

Using the purpose-made constructed targets, further research is warranted in exploring how other factors that are encountered during nocturnal bird surveys, such as artificial lighting, light rain and varying crop heights affect both the thermal imager and image intensifier. By using the targets, quantifiable ranges can be obtained. These quantifiable values can be used to better plan nocturnal surveys, such as knowing how many vantage points are likely to be required, and where best to place them. Also, it would be desirable to assess how both pieces of equipment compare detecting and identifying flying targets. The purpose-made constructed targets are stationary, and fail to assess this aspect.

A common difficulty encountered in both the quantitative and qualitative areas in this chapter was due to the limited number of experienced participants available. Such a small sample may make it difficult to determine statistical significance from the obtained results. For the quantitative field results, this could be improved by carrying out additional trials under similar conditions to increase the sample size, using the same participants if additional personnel are not available. For the questionnaires, additional participants would be required to increase the sample size, if possible.

		Image Intensifier	**Thermal Ima**
Main Strength		Identifying targets	Detecting targ Identifying kn
General Ranges (m)	Optimal Conditions	200-400	300-400
	Fog (50-100 m visibility)	**Detect**: 25-75 **Identify**: 25-50	**Detect**: 175-30 **Identify**: 150
	Full Moon	**Detect**: 225-300+ (300+ with IR lamp) **Identify**: 100-300+ (300+ with IR lamp)	**Detect**: 300+ **Identify**:150-2
	New Moon	**Detect**: 75-300+ (175-300+ with IR lamp) **Identify**: 25-175 (125-200 with IR lamp)	
Weather Effects	Precipitation	50-100 m range. Rain appears to shut out light	Difficulty in ic
	Temperatures <3°	Heat from surveyor causes condensation on the eye piece	
	Wind	Causes image shake	Causes image
Lighting (m)	Light Pollution Behind Device	200-400	
	Light Pollution in Front of Device	70	
Conditions	Favourable Conditions	2-3 hours after sunset and before sunrise <7 inches of crop growth Surveying on a downward slope Wet mud, skyline and open fields	Land in field c Reasonably u sky and open f
	Unfavourable Conditions	Looking against water and woodland Surveying against the sky Dark backgrounds, such as ploughed fields Crop growth higher than 7 inches Low-contrast targets	Cluttered back Similarly shap
Recommended Accompanying Equipment		Tripod Infrared lamp	Tripod

Table 3.9 Summary of image intensifier and thermal imager attributes



1) Detection need met by either device. Target detection is more successful with thermal imager. Target identification is more successful with image intensifier.

2) To best meet detection need and to overcome the limitations of detecting airborne targets it is suggested the thermal imager and image intensifier are used in combination together. This approach may increase the number of identified bird species targets.

Figure 3.10 Flow diagram to provide assistance on the selection of equipment

3.6 Conclusion

There is a growing use of thermal imagers and image intensifiers in nocturnal bird surveys to gather data for Environmental Statements. There is a lack of clear guidance on how to use these technologies, and understanding of their performance which this chapter has sought to address. Past studies to assess strengths and limitations of thermal imagers and image intensifiers for nocturnal bird surveillance exist, but as yet, they have not been closely compared.

The work in this chapter has compared both devices side-by-side empirically, through field trials, and qualitatively, through surveyor experience. A number of findings have been found throughout this chapter, including the effects of weather, landscape, temperature and lighting on image intensifiers and thermal imagers. In addition, maximum detection and identification ranges have been provided for both the thermal imager and image intensifier, based on the field trials and user interviews. This information can be used to help plan future nocturnal surveys. Further research has also been suggested.

It is emphasised that neither night vision technology can replace the other for all survey situations. The choice between image intensifier and thermal imager (or both) is dependent on the survey aims. It is important that when a nocturnal bird survey is being planned that factors such as the purpose of the survey, likely weather conditions, location and species under surveillance are understood, as this will likely affect the choice of night vision equipment and survey technique.

Chapter 4: Comparing a Typical Video Analysis Technique for Nocturnal Bird Flight Activity with a New Proposed Digitised Method

4.1 Introduction

As highlighted from the interviews in Chapter 3, when connected to a video recording system, a thermal imaging camera is ideal for continuously surveying a fixed position, such as airspace, or parts of manmade structures such as communications towers. Video from such surveys is typically collected in full, to be analysed after the survey has been completed. Accuracy rates of visual-based motion detection can be improved by reducing the speed at which the videotape is reviewed. However video recorded using a time lapse video recorded can cause frames to skip when viewed at a reduced speed (Sykes *et al.* 1995).

An alternative approach to reduce the speed of video that has been collected using an analogue time-lapse video recorder is to convert it to digital video. Experience has shown that the newly digitised video can be played back on a computer at a slower rate with no visible frame jumping.

The motivation for this chapter originated from viewing video from a thermal-imager based survey carried out in Cyprus during 2002-2003. As part of an Environmental Impact Assessment for a proposed communications tower, nocturnal bird surveillance based on a thermal imager was used to gather data on bird activity in certain parts of airspace in relation to the proposed tower. The thermal imager was set up to monitor bird interactions within and around an existing communication tower. The thermal imager was positioned at one of three vertical angles each night to monitor different height bands. The surveillance video was collected from a Thales Sophie cooled thermal imager, with a resolution of 320x240 pixels and an 8° lens was attached to a PAL analogue time-lapse video recorder. The time-lapse video recorder was set so that each four-hour videocassette used, stored up to 12 hours of time-lapse footage. The timestamp feature was set on the video recorder, and all of the video collected had a date and time stamp applied. In total, 52 nights of survey data were collected over a two-month period, totalling 520 hours. Once the nocturnal surveys were complete, ornithologists viewed all of the video at real-time.

A sample of the video data gathered for the survey was digitised and viewed on a computer with the playback speed significantly reduced. This approach was taken rather than viewing the video on the time-lapse player at reduced speed as this caused the video frames to jump. It was quickly observed that there were a larger number of targets flying past in the clip than was consistent with a brief comparison made of the number of targets recorded by the ornithologists who originally reviewed the video, highlighting a discrepancy in the number of flying fauna recorded. This generated further interest to explore whether there was a significant difference in flying fauna detections by viewing the video at real-time, as the original ornithologists did and through viewing the video at a slower playback rate.

This investigation is of relevance to other remote surveillance techniques, especially those that use increased playback speed to review collected video as this approach may miss a significant number of bird targets. The primary aims of this chapter, based on the video collected from the Cyprus survey, are to answer the questions:

- is there a significant difference in flying fauna detection rates between viewing samples of the surveillance video at real-time, and at a reduced playback aided by video digitisation, and what may affect this? and
- how much activity from fauna flying in the camera viewshed compared to no fauna activity in the video?

4.2 Method of Technique Comparison

4.2.1 Original Method

Experienced ornithologists viewed each of the videotapes at the original recording speed (i.e. 10 hours viewing for a 10-hour recording). When the observer noticed a flying target, the time and date of the sighting were recorded in addition to other target identifying data, such as size category and if possible, species/group identification, along with estimated distance and heights. Videotapes were viewed in 10 to 15 minute intervals, followed by a five-minute break to reduce the effects of fatigue and eyestrain. The video was viewed on a standard cathode ray tube (CRT) monitor. The observers watched all of the 520 hours of video collected from the survey.

4.2.2 Digitised Reduced Playback Speed

A total of eight video clip samples from the video analysed using the original method were chosen at random for analysis from the 52 survey nights. Each video clip length varied from 20 minutes to 90 minutes in duration, with a total of nine hours of video selected from all of the video collected. Video samples were then converted into the Microsoft Windows Media Video (WMV) digital format, using Windows Movie Maker (version 5.1). This was prepared by initially transferring the video from the VHS videotapes to MiniDV tapes. A MiniDV video recorder was then connected to a computer, and the MiniDV tapes were converted into WMV, using the 'best quality' setting in Windows Movie Maker, with an image size of 640 by 480 pixels. The sampling rate was at 25 frames per second with a variable bit rate[2].

The digitised videos were played using Windows Media Player 10 and were viewed twice as slowly as compared to the original method (half the speed of real-time). This playback speed was chosen as it was the slowest play-back speed available on the Media Player, and this play back software being the one available at the time of the trial. The viewer window was resized so that the observer could comfortably view the whole frame area; this was typically the whole screen. The

[2] Bit rate refers to the number of bits (storage space) required per second to store video. As some parts of the video are not likely to contain any motion such as birds flying past, to conserve the number of bits, the bit rate can vary between saving a few bits to represent a video frame, to many bits to represent motion. This compares to a constant bit rate where the same number of bits are saved per frame, regardless of motion.

video was viewed on a 36.5 centimetre liquid crystal display (LCD) monitor. An LCD monitor was chosen as it has a lower observable flicker (Pätan *et al.* 2002) and was found to reduce the effects of fatigue and irritation on the observers' eyes compared to the CRT monitor due to lower glare, and had a better contrast between the background and bird targets (Krupinski *et al.* 2004). As in the original method, the observer took breaks every 10 to 15 minutes to reduce the effects of fatigue. When the observer noticed a flying target, the time and date of the sighting and the length of time the bird took to cross the camera's field of view were recorded. As only detecting activity was of interest, additional information recorded in the original method was not collected in this instance. The lowest increment on the timestamp was to a second hence precision is at one-second intervals.

4.2.3 Measuring bird flight duration

Flight duration was defined as the amount of time taken by a bird to cross the camera's field of view. The timestamp value on the video was noted at the first instance of the target entering the field of view and at the last instance when the bird left the field of view.

4.2.4 Measuring target size

The method selected for measuring the target size was based on segmenting the bird target and counting the number of pixels of the segmented target. The target pixel size is the relative target size, rather than the absolute size, i.e. the size obtained is not directly related to the actual target size. A large target far away and a smaller target closer to the camera may have the same relative pixel size. The purpose of the relative pixel size is to establish whether the relative target size affects the observer's ability to detect the target. Segmentation involved identifying an object of interest (target in this instance) from a background (sky) and removing the background, leaving behind only the object of interest. The digitised video clips were used for segmentation. Frames containing targets detected were selected in the video clips. The frames were saved as a bitmap (a lossless format) for further processing. Initially each frame was cropped so that the majority of the background was removed, leaving just the target. This was achieved using Microsoft Paint (version 5.1). The segmentation algorithm colour space pre-segmentation from the LTILib computer vision library (LTILib 2005) was then applied to the cropped frames. The colour space pre-segmentation algorithm was selected because during trials it was found to perform best at separating bird targets when compared to other commonly used segmentation techniques (LTILib 2005). The default settings for the algorithm were used, apart from the background tolerance parameter, which was set to 25, based on best tolerance for background pixels. Once the targets had been segmented and separated from the background, the pixels comprising the target were counted using a histogram and recorded.

4.3 Results of Technique Comparison

In total, the original method detected 27 sightings and the digitised, reduced playback speed approach detected 107 sightings from the eight randomly selected video clips. To enable a straightforward comparison of the video clips, the clips were compared by calculating 'sightings per hour'. This was done to compare video clips of differing lengths. Sightings per hour were calculated as:

$$Sightings\ per\ hour = 3600 \cdot \left(\frac{number\ of\ sightings}{video\ clip\ duration\ (\sec onds)} \right) \quad \text{(Equation 4.1)}$$

In order to establish whether differences for results obtained for each method were significant, the two-tailed Wilcoxon Signed Rank Test was used (Zar 1999). The distributions of mean sightings per hour are shown in Figure 4.1. The null hypothesis used was "there is no difference between the number of targets detected using the either viewing method". Applying the signed rank test (α = 0.05), the null hypothesis was rejected (z = 2.37, P = 0.016).

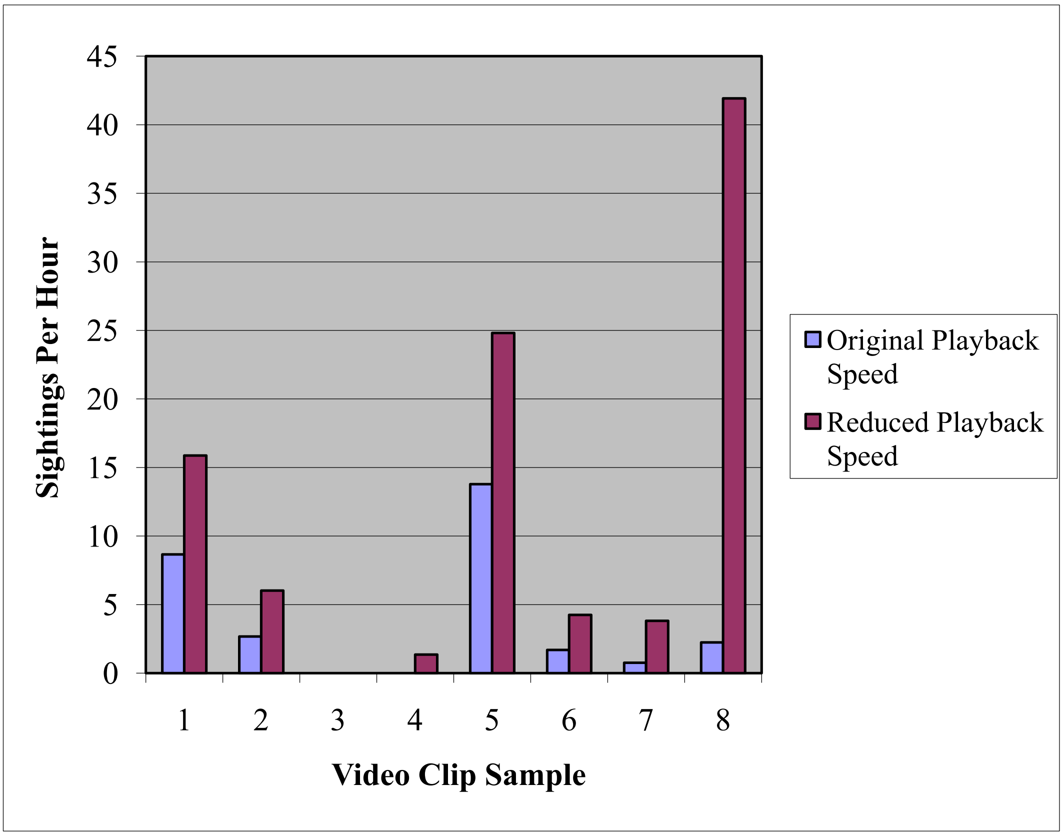


Figure 4.1 Mean sightings per hour for each video clip sample, based on original and reduced playback viewing speeds

The digitised, reduced playback speed method recorded a greater number of targets < 200 pixels in size than the original method (Figure 4.2). Both the original and digitised method found that the majority of targets were < 100 pixels in size. As the targets became larger, frequency dropped off markedly and both methods returned similar detection rates. Both methods suggested that the majority of the targets detected were relatively small according to pixel size.

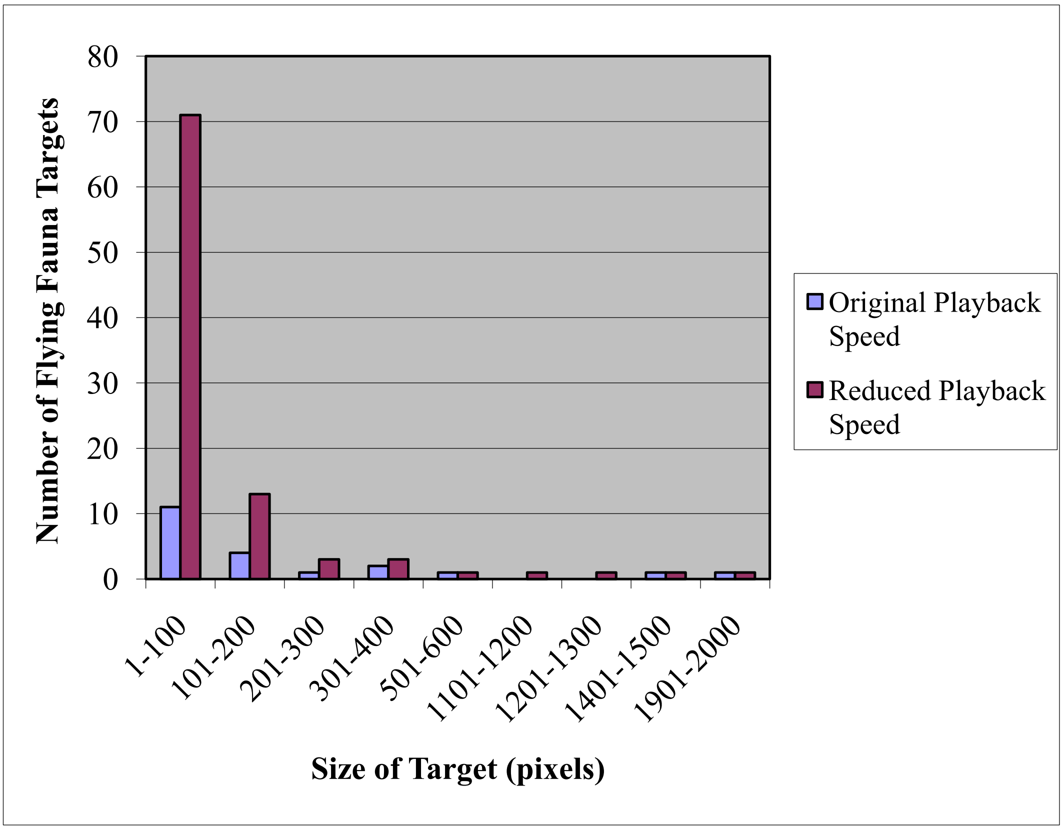


Figure 4.2 Size groupings of targets detected based on original and reduced playback viewing speeds

The majority of the faster moving targets were detected using the digitised method (Figure 4.3). Both methods indicated that the majority of the targets took less than 3 seconds to cross the camera's field of view.

Quantifying the activity of bird targets produced in each of the video clips took into account the length of time each bird target took to cross the camera's field of view and the number of bird targets detected. The targets found using the digitised method were used for determining activity rates. The activity rate for each video sample was calculated as:

$$\%\ Activity = 100 \cdot \left(\frac{total\ video\ time\ with\ bird\ activity\ (\text{seconds})}{video\ clip\ duration\ (\text{seconds})} \right) \quad \text{(Equation 4.2)}$$

For the total 9 hours of data, combining all of the clips used in this study, only 4 minutes (0.7%) contained activity. This is based on using the digitised method.

Assessing each clip individually for activity, the maximum activity time was found to be 2.2% (0.23% standard deviation) for one of the clips.

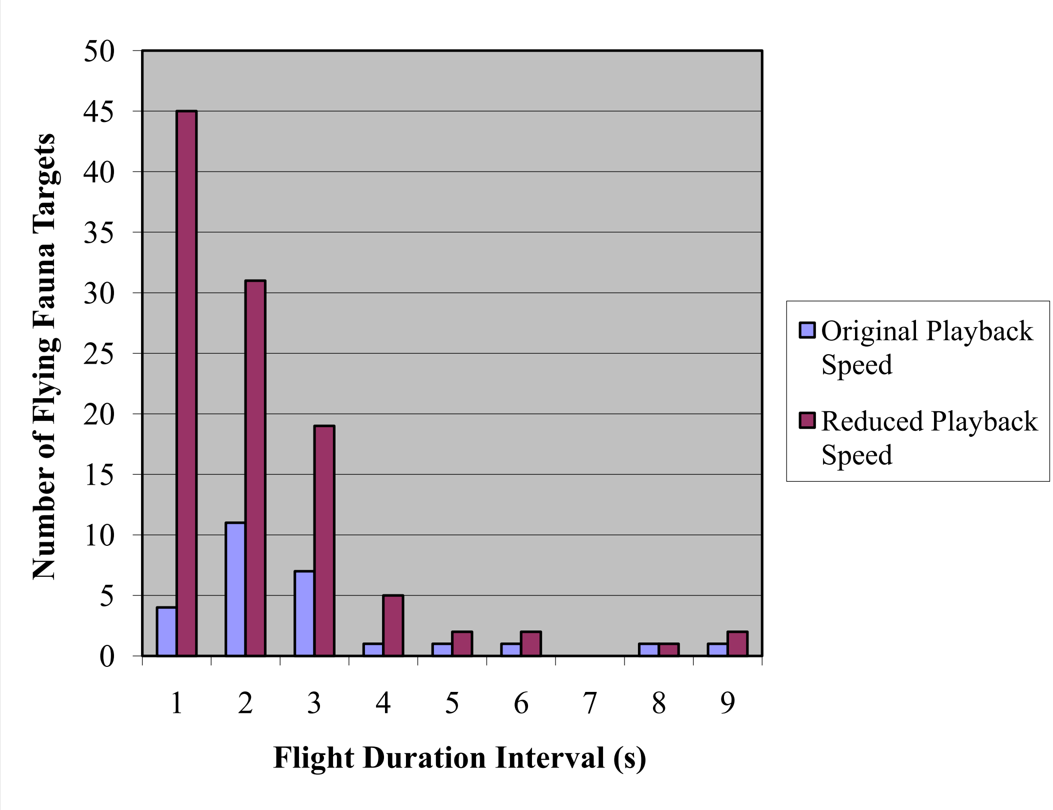


Figure 4.3 Flight duration for each detected flying fauna took to cross camera field of view, based on original and reduced playback viewing speeds

4.4 Discussion of Technique Comparison

The video digitising approach was found to successfully allow the reduction in playback speed without suffering frame jumping.

Using the Wilcoxon Signed Rank Test to compare both methods, reducing the playback speed of the sampled videos (aided by digitisation) significantly increased the number of targets detected.

Comparing the size of targets detected, it was apparent that the smallest size category (up to 100 pixels) was most likely to be detected by reducing the playback speed (with digitisation). In absolute terms, a bird target that was 100 pixels in size for the digitised method is the equivalent to just 0.03% of the total area of the display. The reduced playback speed also detected all of the faster moving bird targets identified using the original method in addition to newly found targets that crossed the screen.

The length of time required for a bird to cross the camera's field of view is in part dependent on the lens size selected for the survey. A wide-angle lens will show a bird taking a longer period of time to cross the field of view as compared to a narrow-angle lens. This is based on the same species of bird flying at the same speed and distance away from the camera. In instances where medium to long-range surveying of distances with thermal imagers (>250 metres) are required, the selected camera lens for the survey is most likely to be narrow-angle to cover the required range. This is due to the low spatial resolution of thermal imaging cameras. Hence it was felt that the length of time taken for a target to cross the camera field of view was relevant as a variable in this instance.

In addition to target size and speed at which a target crossed the camera field of view, the observer could have been affected by fatigue and/or eyestrain as the video progressed. Work by Lavine *et al.* (2002) concluded that as the time on an observation task progressed, the number of targets detected by observers decreased, suggesting observer alertness reducing. Potentially eyestrain or fatigue may have had an affect on the results of either method. However, the use of 5-minute breaks every 10-15 minutes of video viewing was used to reduce the effects.

Based on the results from the digitised, reduced playback speed method, none of the video samples exceeded 2.5% of flying fauna activity. This highlights the large quantity of time that observers using the original method spent monitoring periods of inactivity. For example, in a survey 12 hours in duration, less than 18 minutes of bird activity would be expected based on the maximum value found.

Reducing the playback speed for the viewed samples increased the number of flying fauna detected. A severe limitation with this approach is the extra time required to review the video. Including 5 minute breaks for every 10 minutes of video viewing; every hour of video viewed at original playback speed will take 90 minutes. Every hour of video viewed at half the playback speed will take 180 minutes. This approach does effectively double the amount of surveyor time required to review video, doubling the cost of video analysis. A possible solution to reduce the number of missed targets whilst not significantly increasing the amount of review time required would be to view surveillance video at a reduced speed during periods of peak bird activity, such as at around dawn and dusk.

4.5 Conclusion of Technique Comparison

Video-based surveys are a commonly used approach for collecting large quantities of data from a fixed point. This approach has a number of advantages including reducing the number of staff required on-site, and surveillance data can be reviewed more conveniently.

This investigation into comparing reviewing video at real-time compared to a half the speed of real-time has shown that significantly more flying fauna targets were detected by the reduced speed approach. Both target size and the length of time a target spends on screen appear to have an effect on flying fauna detection rates. This highlights that the use of fast-forward to increase video review speed may decrease target detection rates compared to reviewing the video at real-time, or half real-time. However, this is most likely to occur when monitoring airspace for bird activity.

Reducing the playback speed at which nocturnal bird surveillance video is reviewed effectively doubles the cost of the analysis process. This approach, although in this study it was found to significantly increase the number of flying fauna detected, is essential in order to achieve accurate and comprehensive analysing of thermal imaging video.

The majority of the sampled video clips contain no flying fauna activity. By focusing surveyor attention on just periods of activity from ornithological surveillance video, the efficiency of such approaches would be considerably increased. Chapter 5 goes on to look at computer vision approaches for automating the detection of activity during nocturnal bird surveys.

Chapter 5: Improving the Detection of Flying Fauna through Automated Motion Detection

5.1 Introduction

As highlighted in Chapter 4 using surveyors to view large quantities of nocturnal bird surveillance video is an expensive, error-prone and labour intensive process. Samples of the video assessed in Chapter 4 had no more than 2.5% of running time occupied by flying fauna activity. This highlights large inefficiencies in the use of surveyor's time, as they viewed all of the video.

Using software-based motion detection techniques reduces the amount of surveyor time required to analyse nocturnal bird surveillance video. As discussed in the literature review the thermal threshold-based trigger mechanism used in TADS is sensitive to clouds and cannot adapt. Also failures in the trigger system can lose valuable data. Depending on the failure there may be no other means to review the lost surveillance data.

Maintaining a background model can be used for software-based motion detection. The background model is a representation of an empty scene, and is continually updated based on new incoming image frames. This is useful for incorporating slow adaptations to the scene such as slowly changing cloud cover and introduced objects in the background.

The aim of this chapter was to investigate how software-based motion detection methods could be used to improve the review of nocturnal bird surveillance video gathered from a thermal imager. This was achieved by implementing two motion detection methods and comparing their performance with that of a bird surveyor.

To aid understanding of the automated motion detection methods explored in this chapter, a detailed introduction to these methods is provided in the next section.

5.2 Adaptive Background Models for Motion Detection

5.2.1 Introduction

The two approaches for updating a background model explored in this section are based on running average (McIvor 2000) and cumulative image based temporal templates (Bobick and Davis 2001). Running average maintains a background model and is based on mean values using recent frames to predict the current appearance of the video background scene. New image frames are compared against the background models to determine whether there have been any significant changes. Cumulative image differencing compares how the past few frames compare and whether there is persistent change. Both of these approaches examine temporal pixel variance.

5.2.2 Running Average Overview

There are a number of implementations of the running average background model. This section provides the basis these methods use. The background model maintained by a running average is essentially the mean of a number of past image frames on a per-pixel basis. This assumes each pixel is a Gaussian distribution. New image frame pixels from a video stream are compared with corresponding pixels from the background model to determine whether there is a difference between the two. A difference suggests there is motion occurring in the image frame. As there may be slight variance between corresponding pixels in the background model and image frame that do not necessarily mean a change, a threshold is used to suppress false differences. The threshold used can either be based on a predetermined fixed value, or an adaptive value based on the standard deviation for the corresponding pixel in the background model (McIvor 2000). If standard deviation is used, a separate model is also maintained and updated with the background model.

In Figure 5.1, the Gaussian curve represents the probability distribution of a background pixel, stretching horizontally across pixel intensity (greyscale) values. B marks the mean value of the pixel. Three scenarios of a new corresponding image pixel are presented ($I^{1,}$ I^2, I^3). The intensity value I^2 falls within the fixed threshold range (T). The intensity value of I^3 falls within the standard deviation (multiplied by a constant K) range (σ). Based on the threshold used, I^3 and I^2 would be classed as part of the background model. As I^1 falls within neither threshold, it would be considered a new detection. Once the new image frame pixels have been classified, it is used to update the background model.

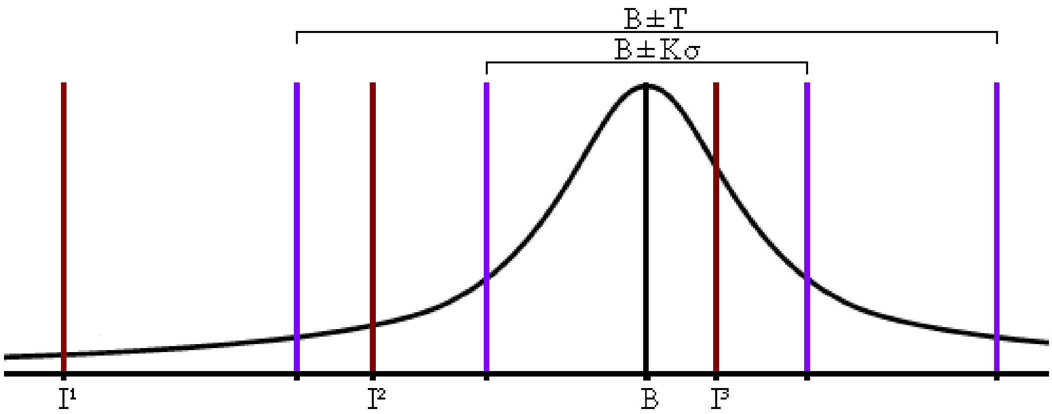


Figure 5.1 Single pixel running average background distribution (B = mean). $I^{1,}$ I^2, I^3 = image pixel intensities, T = fixed threshold, σ = standard deviation, K = constant

The rate at which the background updates is based on the learning rate. The background model is updated using:

$$B_{t+1} = (1-\rho)B_t + \rho I_t \qquad \text{(Equation 5.1)}$$

where B_t is the current background, I_t is the current image frame, ρ is the learning rate and B_{t+1} is the updated background. With ρ=0.05, if a new feature is introduced at frame (n), provided that the feature is stationary and does not move, it will be incorporated into the background model at frame (n+20). As the background model can adapt very quickly, background initialisation is not important, as the model will adjust accordingly. For this reason, the initial frame used for the background model is usually the first image frame.

Incoming image frames are compared against the background model on a pixel-by-pixel basis. Once the difference has been calculated, a threshold is applied to determine whether each pixel belongs to the background, or is a foreground object (i.e. a bird target):

$$|I_t - B_t| > T \qquad \text{(Equation 5.2)}$$

where T is a threshold value. The threshold value can either be a fixed value for all pixels or one that varies based on standard deviation. If standard deviation is used, an additional 'model' is maintained and updated, using:

$$\sigma_{t+1}^2 = (1-\rho)\sigma_t^2 + \rho(B_t - I_t)^2 \qquad \text{(Equation 5.3)}$$

where σ_t^2 is the current variance and σ_{t+1}^2 is the updated variance. Hence, thresholding with standard deviation uses:

$$|I_t - B_t| > K\sigma_t \qquad \text{(Equation 5.4)}$$

where K is a constant.

Using a fixed threshold does not require additional computational work. The fixed threshold can be more robust to spurious pixel values depending on the value chosen, at some expense of how accurately the target object is separated (segmented) from the background. A threshold based on standard deviation may improve object segmentation accuracy, but does require more computational processing. Also, past experience trialling this approach has shown that standard deviation-based thresholding can be over sensitive, falsely marking background pixels as foreground objects.

5.2.3 Cumulative Image Differencing (Based on Temporal Templates)

The overall aim of detection based on cumulative motion is to accumulate a set number of pixels recognised to be different from the background. Firstly, the current frame and the last frame are differenced from each other (image differencing), and any pixels that exceed a specified threshold are marked as foreground objects. To make image differencing more robust to small changes, a specified number of differenced images can be compared to see whether there is continual marking of pixels as foreground objects. If there are, this is classed as motion. The implementation of cumulative image differencing used in this chapter is based on LTILib implementation of Temporal Templates (LTILib 2005) by Bobick and Davis (2001). Bobick and Davis use this approach to generate a motion energy image that shows an action template (a superimposition of all the frames of an object's motion), and a motion history image that shows the historic motion using varying shades of grey (Figure 5.2).

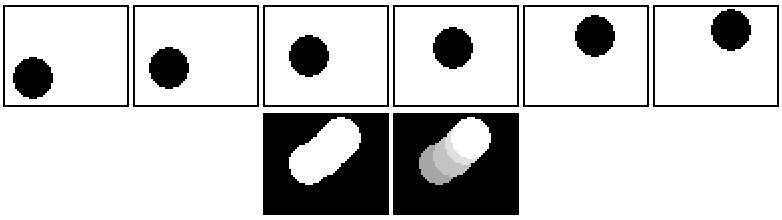


Figure 5.2 Temporal templates example. Top: a series of frames showing a moving blob. Bottom: left – motion energy image based on τ =3, right – motion history image based on τ =3

Firstly, a binary image is obtained using the image differencing approach suggested by Bobick and Davis (2001):

$$D(x,y,t) = \begin{cases} 0 \; if \; |I_t - I_{t-1}| \le T \\ 1 \; otherwise \end{cases} \qquad \text{(Equation 5.5)}$$

where $D(x,y,t)$ is the resulting binary image (t refers to a sequence of binary images), I_t is the current frame, I_{t-1} is the previous frame, and T is a threshold (Equation 5.8).

Bobick and Davis (2001) define the motion energy image as:

$$E_\tau(x,y,t) = \bigcup_{i=0}^{\tau-1} D(x,y,t-i) \qquad \text{(Equation 5.6)}$$

where τ is the number of frames required to be accumulated. The motion energy image represents the motion that an object made, but does not define where the motion started, or in which direction. The motion history image can provide a temporal aspect of motion, and is generated using:

$$H_{\tau}(x,y,t)=\begin{cases}\tau \text{ } if \text{ } D(x,y,t)=1 \\ \max(0,H(x,y,t-1)-1) \\ \quad otherwise\end{cases} \qquad \text{(Equation 5.7)}$$

Either the motion energy image or the motion history image can be used to detect motion by cumulative motion.

A limitation with this method exists if a target moves across the scene in less than τ frames.

5.3 Experiment to Compare Visual and Automated Motion Detection

Having introduced two automated motion detection approaches, these methods are going to be compared against a human observer to determine target detection accuracy rates.

As the thermal imager is always stationary, there is no need to deal with how observed objects move with respect to the imager. In addition the background will largely be stationary, with only foreground objects creating motion. Hence approaches that look for differences between frames would be the most applicable in this situation. Issues that commonly plague background subtraction techniques such as sudden changes in illumination and shadows are not likely to cause problems as they are largely unperceived by a thermal imager. Further information describing the application of the thermal imager for collecting nocturnal bird surveillance video is described in Appendix E. The ability to deal with gradual changes in background such as changes in ambient temperatures is useful and the two approaches outlined above were chosen based on these conditions.

An adaptive background approach in the form of running average was chosen as it maintains a background that updates gradually to change. It can also be used for foreground object segmentation using the background model. Cumulative image subtraction is also computationally inexpensive, and as continuous change between three frames is sought, changes to background will soon be ignored if they are not consistently in motion. Both approaches were rapid in their implementation and do not require special initialisation apart from masks to block any continual motion that may be in the scene.

To reduce the effects of sharp edges visible in the video causing false motion each frame was smoothed with a Gaussian kernel, width = 3, standard deviation = 1. This small level of smoothing was chosen to preserve edges without causing a large degree of image distortion. Keeping the kernel size small reduced the computational expense of the smoothing procedure. The learning rate of 0.05 has been commonly used in other background modelling approaches (e.g. Stauffer and Grimson 1999, McIvor 2000). At 0.05, 20 consecutive frames are required to integrate a new stationary change into the background model. A learning rate that is too large may miss slow-moving or distant bird targets as they would be incorporated into the background model. A learning rate that is too small make cause new background objects to be falsely identified as moving objects until they added to the background model.

The minimum number of frames required for cumulative differencing is three. If too many frames are chosen, fast moving targets, such as birds moving close to the camera may be missed as the number of frames they generate to move across the screen may be fewer than the number of frames used for cumulative differencing. Three frames should be adequate for missing pixel noise as that would happen randomly on a per frame basis, and not likely to occur continuously over consecutive frames.

5.3.1 Test Data

Two one-hour video clips captured using thermal imagers from nocturnal surveillance projects were used to compare motion detection techniques. The first clip consists of a relatively clear scene, with the camera field of view mostly covering sky. Towards the end of the hour, clouds sweep into the field of view. The second video clip consists of a relatively cluttered scene. The camera field of view is looking over a field with a lake in view, and trees in the distance (Figure 5.3).

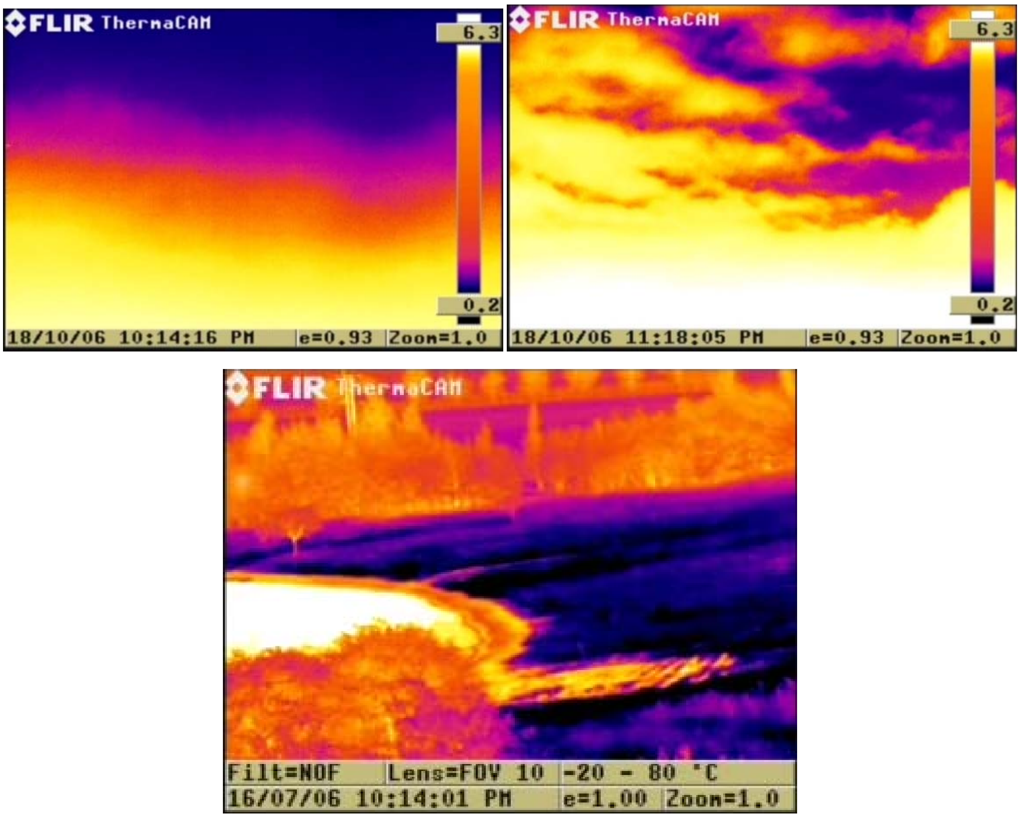


Figure 5.3 Screen shots from the video clips. Top: video clip one with clear sky (left), and as it gets progressively cloudier (right). Bottom: video clip two

Video clips one and two were collected from a FLIR ThermaCam SC3000 using a 10° lens. Both video clips were recorded directly onto a laptop computer using a digital frame grabber connected to the thermal imager's video out socket.

5.3.2 Method for Surveyor-Based Manual Fauna Motion Detection

A surveyor was provided with video clips one and two to review at normal (real-time) playback speed. The video clips were viewed on a 14" LCD monitor, using Microsoft Windows Media Player 10. Each clip was sectioned out into ten-minute samples. Following each ten minutes of video viewed, the observer would take a ten-minute break away from viewing the video. In case of motion, the surveyor was instructed to pause the video playback, and record video time stamp, direction of fauna travel and any additional comments. If more than one fauna was viewable in the video clip at any one time, the surveyor was instructed to record the additional detections. In total, the surveyor assessed 12 10-minute video samples.

5.3.3 Running Average and Cumulative Image Differencing Methods Applied to Automated Motion Detection

Video clips one and two were used to test the running average and cumulative image differencing methods. A binary mask was created for each video clip that concealed the time-stamp image logo, edges and temperature bar in the video clips. This was to remove known potential motion, and possible edge noise from parts of the image (Figure 5.4). The masks were drawn by hand in Microsoft Paint (version 5.1) using a frame captured from each video clip as a guide.

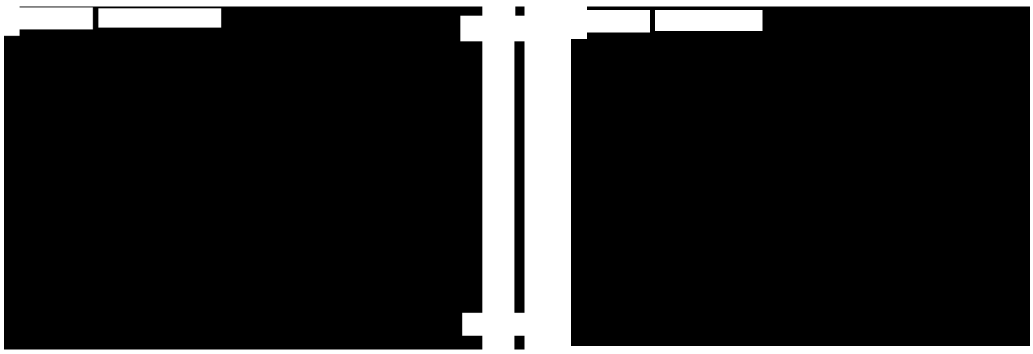


Figure 5.4 Masks used for video clip one (left) and video clip two (right)

Each image frame was converted to 256 greyscale level images. To reduce the effects of spurious pixel noise, each frame was spatially convoluted with a Gaussian kernel (3x3 kernel, standard deviation=1).

Running Average

The running average method used in these trials was implemented in the LTILib computer vision library. The background was modelled on (Equation 5.1). Two different fixed thresholds were trialled (Equation 5.2), T = 18 greyscale levels and T = 26 greyscale levels. The learning rate (ρ) of 0.05 was used for both trials. Motion detection was defined as any pixel from any frame returning a value that exceeds the fixed threshold values. A fixed threshold was chosen as experimental work looking at the use of a standard deviation based threshold revealed a high sensitivity to small fluctuations in pixel intensity which was not a result of motion, thereby 'detecting' a high degree false motion. There is also a computational processing advantage as the standard deviation for every pixel in the image for every frame does not need to be calculated. As a moving bird target emits heat compared to the background it is moving against, there will be a number of intensity levels difference between the bird target and the background. Having trialled a number of intensity levels, a threshold set at 18 greyscale levels was found to offer good segmentation of a moving target from the background without being too sensitive to small changes to individual pixel intensities, although other nearby values are likely to also achieve this. A threshold at 26 greyscale levels was chosen to see how it compares to 18 greyscale levels.

Cumulative Image Differencing (Based on Temporal Templates)

The temporal template function was used from the LTILib computer vision library (LTILib 2008b). The parameters used were τ = 3, ‘average of difference’ for the threshold value was enabled. The average of difference threshold value is calculated for every frame used by the LTILib computer vision library, and is determined as follows:

$$T_{t+1} = \frac{\sum \left| I_t(x,y) - I_{t-1}(x,y) \right|}{wh} \qquad \text{(Equation 5.8)}$$

where w and h are the width and height of the frames in pixels. Motion detection was defined as any frame that generates a motion history or motion energy image (see Section 5.2.3). The LTILib threshold was trialled with several video clips and was found to work well and hence kept.

Each time motion was detected by either method, the image frame that caused the detection was saved, along with the thresholded, segmented image that triggered the detection.

Once the above methods had been run, all of the frames generated for each method were reviewed by the author. The video clip time stamp was recorded, and a check made to see whether the frame was a product of a true detection (caused by fauna), or a false detection. An interval of one second between different frames (as determined by time stamp) was treated as a new trigger event. If multiple targets were observed on the segmented images, they were counted as individual targets. If no fauna was visible in the segmented images, or it was likely that other sources caused the motion (such as clouds), even if the fauna was present, the detection was recorded as false.

5.4 Results of Comparing Visual and Automated Motion Detection

The number of detections per method for each 10-minute video sample was tallied together for each video clip. A comparison of target detections is presented in Figure 5.5 (video clip one) and Figure 5.6 (video clip two).

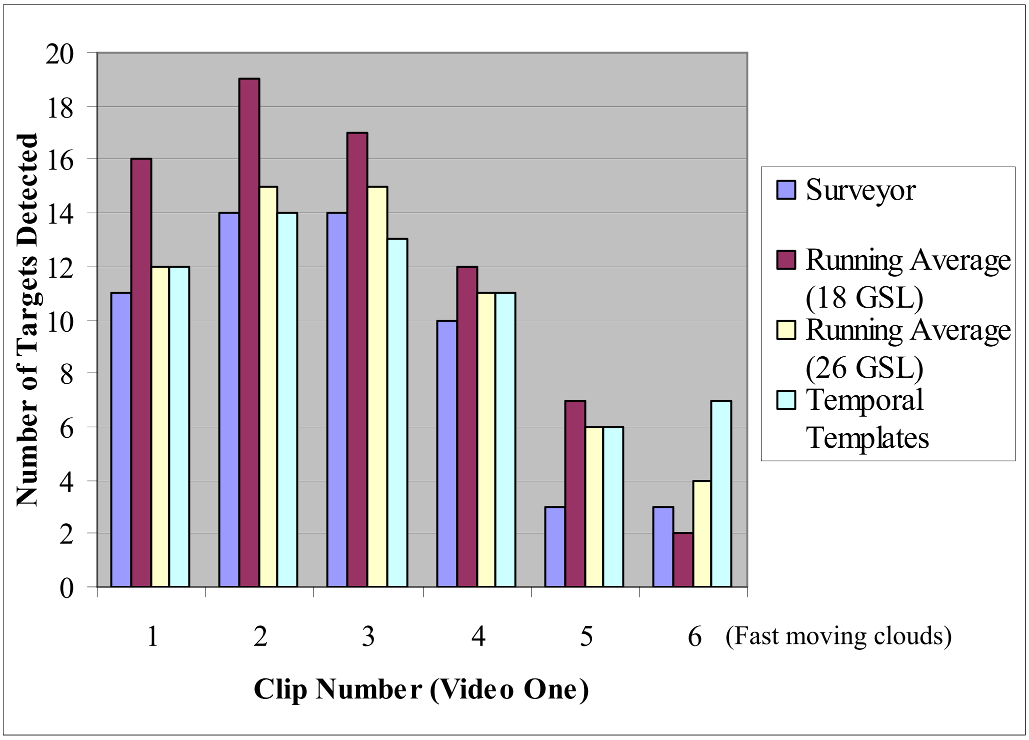


Figure 5.5 Number of targets detected in video one for each method. GSL = Greyscale Level

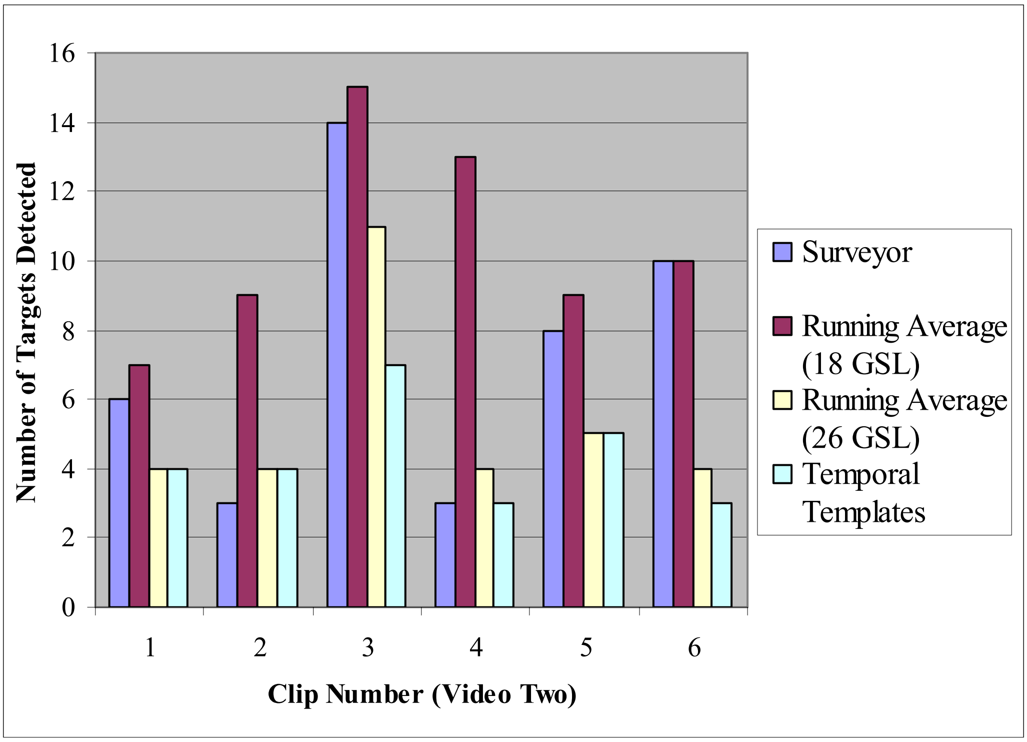


Figure 5.6 Number of targets detected in video clip two for each method. GSL = Greyscale Level

In video clip one the running average method also falsely detected motion, caused by fast moving clouds (Table 5.1). Some of the false triggers lasted hundreds of frames (spanning a couple of minutes). Any flying fauna crossing through during these periods of false triggering would have been discarded with the false motion. No frames were falsely detected in video clip two.

Video Sample	**1**	**2**	**3**	**4**	**5**	**6**
T = 18	1	0	4	1	10	33
T = 26	0	0	0	0	0	10

Table 5.1 False detections from running average method in video clip one. T is the greyscale threshold level

5.5 Discussion of Comparing Visual and Automated Motion Detection

Both the running average and temporal template methods detected significantly more fauna targets when compared to the surveyor in the majority of the samples. The implemented running average method detected the most number of targets, but also succumbed to false triggers, mainly due to fast moving clouds. A target moving across the camera's field of view in less than the number of frames used to accumulate a model for temporal templates is a possible explanation for the missed detections. The fixed threshold used with the running average had an effect on detection rates, with T=18 greyscale levels detecting more targets compared to T=26 greyscale levels but the larger of the two thresholds had less false detections. Cluttered scenes, such as those observed in video clip two did not appear to increase false detection rates. The temporal templates method suffered from no false detections from either video clip, and during the period of fast moving clouds, out-performed the running average method.

5.6 Conclusion of Comparing Visual and Automated Motion Detection

The software-based motion detection techniques presented in this chapter were found to be more effective at detecting moving targets when compared to the surveyor. Apart from drawing the initial mask (Figure 5.4) and reviewing the detection frames, no additional surveyor time was required to review the video.

For a relatively still background scene (regardless of clutter) the running average approach is recommended for maximum target detection. In scenes likely to have fast-moving clouds, the temporal templates approach is recommended, at the potential cost of some missed targets.

A video analysis program incorporating both motion detection approaches is currently being used by RPS. The surveyor has a look at the video to decide which motion detection technique would be most appropriate to use. Any areas in the video where the background is continuously in motion, such as rotating wind turbine blades or a busy road are blocked out with a hand-crafted mask. Any motion detected is saved as image frames with accompanying time-stamp for the surveyor to review.

Automating motion detection can speed up analysis of flying fauna surveillance video by removing the need of a surveyor to manually review the video. The techniques suggested in this chapter all outperformed the surveyor in detecting targets from video clips. However, these techniques will detect any motion. The unique characteristic of oscillating wings separates birds and bats from other objects or targets that could cause motion detection. By successfully identifying wing flapping, it may be possible to correctly classify detected targets as flying fauna, further reducing the number of targets detected. Chapter 6 looks at approaches that can be used for classifying this periodic motion.

Chapter 6: Approaches to Using Periodic and Cyclic Motion Detection Methods to Detect Flying Fauna

6.1 Introduction

As highlighted in Chapter 5 many types of fauna can trigger motion detection. In addition, other objects, such as fast-moving clouds and aircraft can also cause the recording of motion. The means by which birds and bats fly through wing oscillations makes them distinguishable from other airborne objects. This unique characteristic can be used to filter out bird and bats from other objects that cause false motion detection. Another benefit of identifying objects exhibiting periodicity would come from automating the masking of rotating, fixed structures, such as wind turbines. Currently, hand-drawn masks are used to block out wind turbine blades (Desholm 2003). Although this is a fast and simple solution, should the camera be moved, either accidentally or through wind shake, the turbine may no longer be obscured by the mask (Desholm 2003), causing false motion.

Periodic or cyclic motion can describe bird and bat wing-flapping (or wing beat) motion. Periodic motion or periodicity is defined as a motion or action that is regular and repeats in equal time intervals. Examples of periodic motion include a swinging pendulum, a metronome, or a person walking with regular strides. Objects may also exhibit cyclic motion. The definition of cyclic motion used in this and subsequent chapters is defined as a motion that is regular and that repeats, but not necessarily with equal time intervals. Examples of cyclic motion include an irregular heartbeat, rising and falling tide, or seasonal weather. In Figure 6.1, the sinusoidal and square waves repeat periodically. The motion is regular and repeats at constant time intervals. The cyclic curve and square wave in Figure 6.2 repeat, but not with a fixed period, they repeat cyclically.

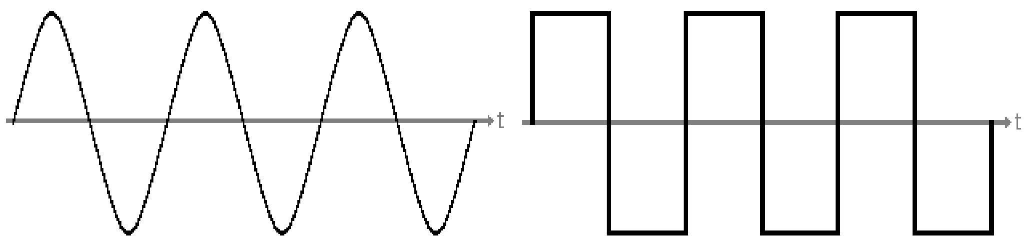


Figure 6.1 Examples of periodic motion

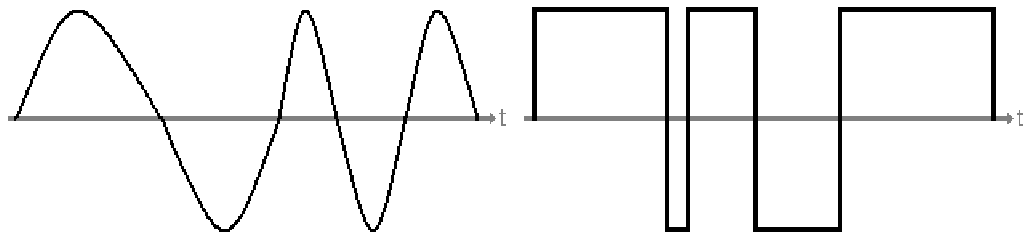


Figure 6.2 Examples of cyclic motion

Bird wing-flapping can be periodic or cyclic, depending on species and flight behaviour. Birds may be soaring (wings outstretched), taking off in flight, avoiding obstacles, or settling into flight (Tobalske 2007). Table 6.1 highlights how bird flapping can differ across species, showing how flight style can vary greatly.

Species	**Description of flight**
Golden Plover *Pluvialis apricaria*	Flight rapid and confident, but with less graceful and fluid action than small waders and noticeably regular wing-beats.
Pink-footed Goose *Anser brachyrhynchus*	Wing-beats faster and more fluid than larger species.
Herring Gull *Larus argentatus*	Active flight strong, buoyant, and usually direct, with deep, powerful wing-beats. Soaring and sailing ability marked whether over sea or breeding habitat.
Rook *Corvus frugilegus*	Flight variable: around colony, remarkably agile; less accomplished when moving between feeding areas, with direct and deliberate progress along regular paths achieved by fast-flapping and slightly laborious action with more regular wing-beats and less gliding than in Carrion Crow.
Buzzard *Buteo buteo*	Soars with wings raised in shallow **V** ... glides on flat. Gliding flight interspersed with series of rather fast, stiff, shallow wing-beats, lacking looseness and depth of beat of most other medium-sized raptors. Will actively hover at times; often hangs on wind.
Starling *Sturnus vulgaris*	Flight swift and usually notably direct ... action combines rapid beats of triangular wings with occasional glides and momentary closed-wing attitudes producing level shooting progress; over short distance and in tight spaces, wheels and sweeps, but still retains shooting element. When hawking for flying insects ..., flight slower and more graceful.

Table 6.1 Species and description of flight. All descriptions of flight are quoted from Snow and Perrins (1998)

The aims of this chapter were to look at how some existing periodic motion detection techniques may be applied to flying fauna targets, and how they can be adapted for detecting cyclic motion. This was achieved by:

- trialling two periodicity detection techniques on real periodic data; and
- assessing how the most promising method dealt with synthetic and real cyclic data.

6.2 Overview of Two Periodic Motion Detection Approaches

6.2.1 Periodic Motion Feature Analysis

Methods based on periodic motion feature analysis work on identifying measurable features, such as limbs in an image. These features are monitored, and are assessed for periodicity as they change over time. The periodic motion feature analysis approach focused on in this chapter is based on Niyogi and Adelson (1994).

Niyogi and Adelson's method initially stacks all of the sourced images in sequential order, forming an image cube (X, Y, T). X and Y represent the spatial component of the image block and T represents the images over a time interval. An example of this is shown in Figure 6.3. To create the XT slice, a section is selected along the y-axis (illustrated by the black line 1/3 up from the base of the image). It is this XT slice that is used by Niyogi and Adelson to determine periodic motion.

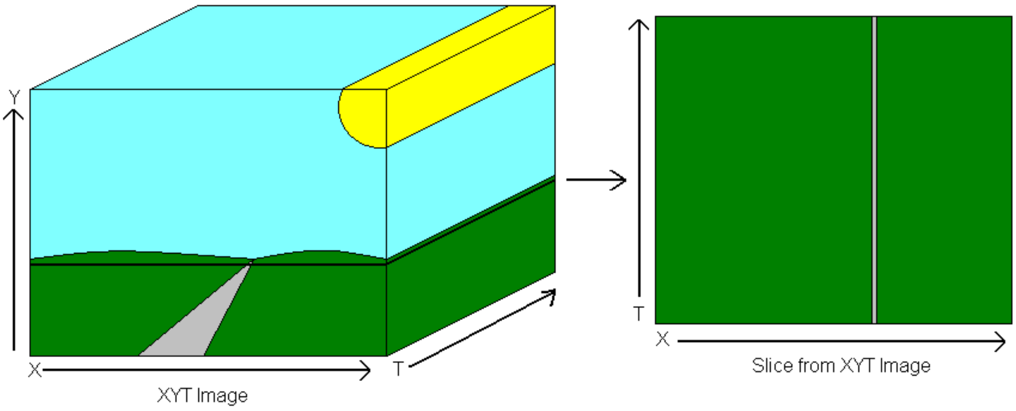


Figure 6.3 An image cube comprising of many frames stacked over time

6.2.2 Object Similarity Periodicity Analysis

Methods based on object similarity look at how a whole object, as one entity, changes temporally. This is achieved by comparing the object with itself over time. An approach used by Cutler and Davis (2000) and Plotnik and Rock (2002) for object self-comparison is through the use of similarity matrices.

A similarity matrix is a way of determining relationships between signals, or a single signal (self-similarity). This method can provide a visual or numeric representation of correspondence within the signal, displaying a relationship between signals or within a signal. An illustration of how a similarity matrix can be used for comparing how a series changes temporally is shown in Figure 6.4.

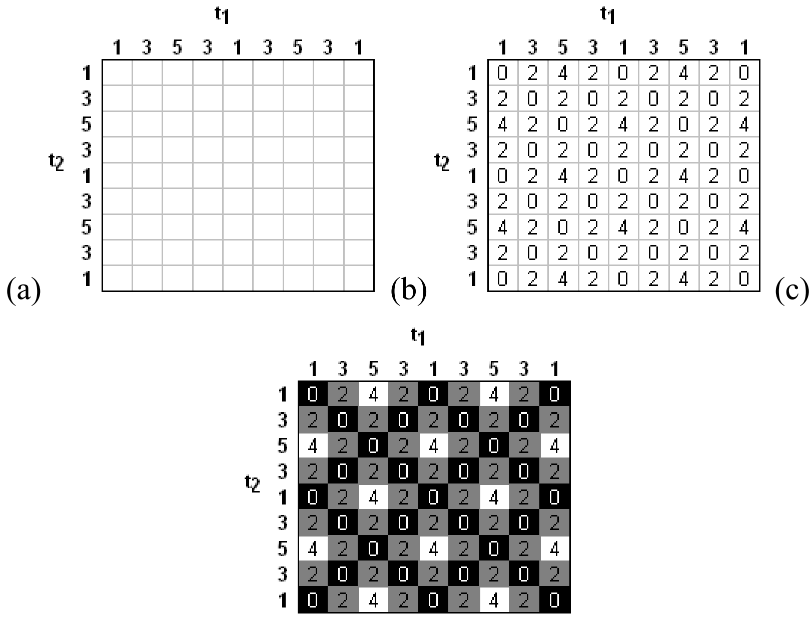


Figure 6.4 Similarity matrix illustration using a number series. a) The series plotted against itself. b) Series terms differenced over time. c) Colour-shading of elements to provide a visual interpretation

An oscillating numerical series of {1, 3, 5, 3, 1, 3, 5, 3, 1} is plotted against itself in a similarity matrix (Figure 6.4(a)). The result of the difference for each term over time is placed in each element (Figure 6.4 (b)). The lower the difference, the more similar the terms of the series are, and the larger the difference, the more different they are. A repeating pattern within the matrix suggests a periodic or cyclic relationship is present within the series. To enhance the visualisation of any periodic or cyclic relationship, a shading reference for the elements is provided. Black represents zero and white represents the maximum difference (four in this instance, Figure 6.4(c)). Measuring the number of elements between crossover peaks of similarity (black elements, areas where motion has repeated as the pattern has returned to the point where it is most similar with its initial state) identifies how often the series repeats (every four elements in this instance).

The motion feature based approach was trialled to see how looking specific target features (such as flapping wings) can be observed over time to detect periodic motion. Feature-based observation is a typically used approach, as outlined in the literature review.

The similarity matrices approach was chosen as the orientation of the bird target it is applied on is irrelevant. This is important as when a bird is in flight, it has freedom in all three dimensions, as this freedom in movement could make it very difficult to locate features such as a head, wings or the body. This approach compares favourably to the other methods described in the literature review which rely on locating and tracking specific target features to work.

6.3 Method for Trialling Periodicity Detection

6.3.1 Method for Periodic Motion Feature Analysis

A volunteer walked across a relatively stable, cluttered scene at a constant pace. To represent the motion of a bird, the volunteer flapped his arms as he walked across at a constant pace. White markers were used to distinguish the volunteer's arms from his clothing (Figure 6.5). The volunteer maintained a parallel path with the camera. This removes the need to apply alignment correction for movement across the Y-axis.

Figure 6.5 Volunteer flapping

A total of 40 frames were generated. The frames were stacked together sequentially to create an image block (standard x-y axes with the third axes, t representing temporal changes). The height (y) values selected corresponded to the location of the volunteers' ankle and upper arm when lowered. At these points the two XT slices were extracted.

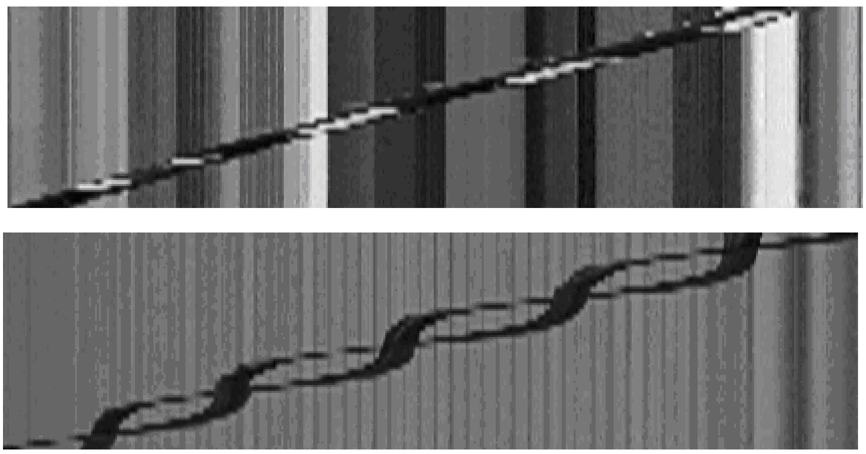
6.3.2 Results for Periodic Motion Feature Analysis

Figure 6.5 (a) shows the XT slice extract with the lowered arm with the marker, and Figure 6.6 (b) shows the XT slice extract at the ankle level. The braiding pattern is visible at the ankle slice after applying the transform. The crossing points of the braid represent when the volunteer's ankles cross whilst walking. Half the walking period is obtained by measuring the pixel distance between the braid crossing points (the full period occurs when the legs are back at their original position). Calculating the period (T) of the walking is as follows:

$$T = \frac{2dT}{Fr} \qquad \text{(Equation 6.1)}$$

where Fr = frames per second, and dT is the number of vertical pixels between where the ankles cross.

The arm-level slice shows a white dashed line, with the white originating from the marker worn by the volunteer. The dark black line between the dashes is from the volunteer's dark clothing. (Equation 6.1) can also be used to calculate the period, using the measured distance between white dash midpoints to the midpoints of the following black dash, and dividing by the frames per second.



(a)

(b)

Figure 6.6 XT slices. (a) arm level slice (b) ankle level slice. Both slices have been stretched for illustration

6.3.3 Method for Object Similarity Periodicity Analysis

Two sets of data were used to investigate area-based differencing. The first set is used to model the varying heat intensities a bird may produce as it flies across the thermal imager viewshed. This ‘blinking’, is caused when the warmer body of the bird is shielded from the thermal imager by cooler wings as the bird flaps. This variance in heat during flight is modelled by changing the intensity of a dot over time. Gaussian noise was added to the blob (standard deviation = 5). The rate of change between light and dark is not completely linear (Figure 6.7(a)). The blob returns to light intensity every 22 frames. A total of 50 frames are used. A thermal recording of a rotating wind turbine was used to create the second set of data. The turbine frames are pre-processed using a binary threshold. The threshold removes the majority of the frame background, leaving the turbine as the foreground object. (Figure 6.7(b)). The turbine assumes the same position every 33 frames. A total of 150 frames were used.

(a)

(b)

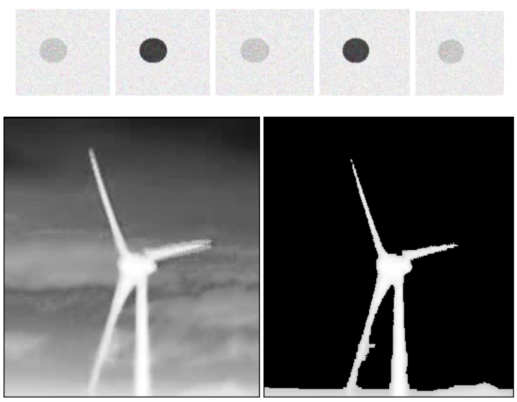


Figure 6.7 The test data. (a) The dots with changing intensity. (b) The rotating turbine and the turbine with a threshold applied

Differencing was applied to each set of data. Each frame in time was differenced as follows:

$$S_{t1,t2} = k\sum\left|O_{t1_{(x,y)}} - O_{t2_{(x,y)}}\right| \qquad \text{(Equation 6.2)}$$

where S is the similarity matrix element at position (1,2), t1 and t2 represent the period between the frames, k is a threshold constant, 0.01 used in this example, and O is the frame. A threshold constant was used to improve the visual contrasts within the generated similarity matrix. The S values were translated to 8-bit greyscale values. A threshold constant was used to improve the contrast of the matrices. Prior to applying the threshold constant matrices would appear very dark. For the data set constant of k=0.01 was used as it sufficiently altered the contrast. A more appropriate approach for improving matrix contrast is through histogram-based contrast equalisation. This approach removes the need to pre-define values and hence flexible on all matrices and this approach was used for following work found in Chapter 7. Object segmentation was achieved using the background modelling approach described in the previous chapter.

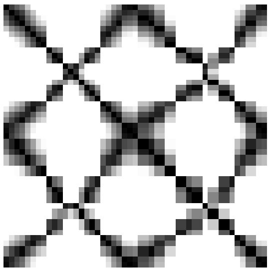
6.3.4 Results for Object Similarity Periodicity Analysis

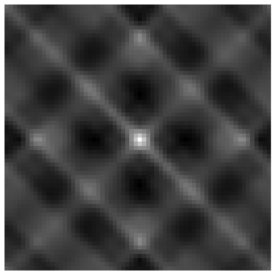
The similarity matrices for the intensity-changing dot and for the turbine are shown in Figure 6.8 and Figure 6.9. Pattern repetition is evident in both similarity matrices, which indicates the object has reoccurring activity/phases. Periodicity in the form of clearly visible lattices is observed from the dot example. However, identifying the reoccurring periodicity pattern from the turbine similarity matrix is less straightforward. Autocorrelation enhances repeating patterns. The autocorrelation image for both similarity matrices can be viewed in Figure 6.8 (b) and Figure 6.9 (b). Measuring the distance between correlation peaks identifies the period of the motion in pixels. Fourier analysis can be applied to a similarity matrix to identify the most common frequency. This is illustrated in Figure 6.8 (c) and Figure 6.9 (c). The peak frequency for the peak amplitude indicates the most likely frequency for the object's motion. Applying a Fast Fourier Transform (FFT) is used to generate a power spectrum. ImageJ (NIH 2008) was used to generate the Fourier transforms and autocorrelation images. The period (T) of the objects motion from the power spectrum can be calculated using:

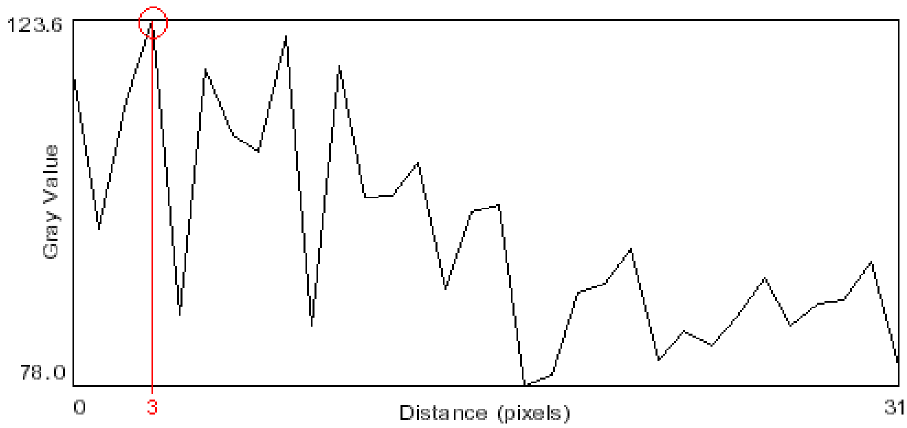
$$T = \frac{X_f}{F} \qquad \text{(Equation 6.3)}$$

where X_f is the length of the FFT image in pixels, and F is the frequency of the maximum amplitude from the power spectrum in Hz.

Using (Equation 6.3) to calculate the period from the power spectrum, for the dot, T_d = 64/3 = 21.3 seconds, compared to the known periodicity of 22 seconds, and for the turbine, T_t = 256/8 = 32 seconds, compared to the known periodicity of 33 seconds. Only the positive quadrant of the FFT image is used to generate the power spectrum for positive frequencies.


(a)


(b)



(c)

Figure 6.8 (a) The similarity matrix for the dot over 50 frames (b) the autocorrelation image of the similarity matrix (c) The positive quarter of the FFT power spectrum of the similarity matrix. The peak is highlighted, and the frequency (F) is found to be 3 Hz

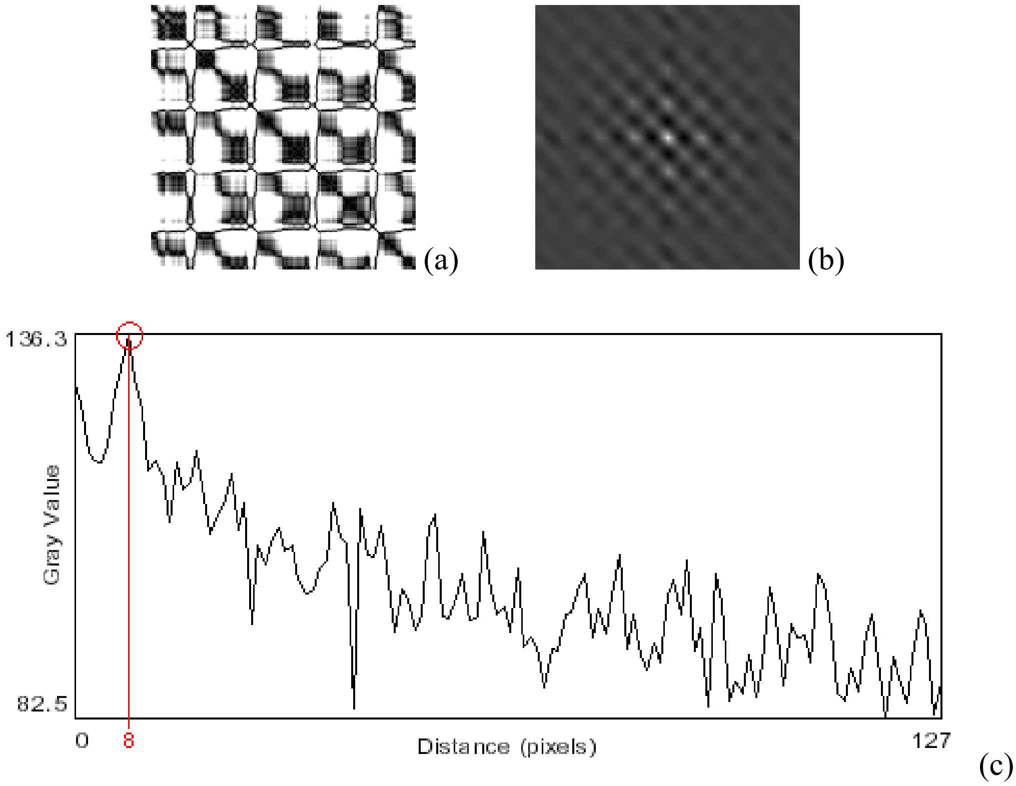


Figure 6.9 (a) The similarity matrix for the turbine over 150 frames (b) the autocorrelation image of the similarity matrix (c) The positive quarter of the FFT power spectrum of the similarity matrix. The peak is highlighted, and the frequency (F) is found to be 8 Hz

6.3.5 Discussion of Trialling Periodicity Detection

A distinct braiding pattern was generated from an ankle XT slice using periodic motion feature analysis. The XT slice at the arm level was not as successful, producing only a dashed line. Also, variability in crossover distance is likely to occur. Object similarity periodicity analysis indicated periodic motion using the two test examples. Applying autocorrelation to the similarity matrices further enhanced the visible periodicity. Power spectrum analysis of the matrices provided a straightforward method for object motion periodicity detection.

6.3.6 Conclusion of Trialling Periodicity Detection

Initial trials suggest that the use of object similarity periodicity analysis, based on similarity matrices, offers a flexible approach for representing flying fauna based on intensity changes. The wind turbine example also provided a distinguishable pattern. By using the frequency and pattern generated by the turbine, it may be possible for an automated vision system to ignore it altogether as a background object.

6.4 Using Similarity Matrices to Represent Cyclic Motion

6.4.1 Cyclic Motion Introduction

Initial success with the application of similarity matrices to periodic data has prompted the investigation of generating matrices from cyclic data. The Cutler and Davis (2000) approach for analysing similarity matrices assumes periodic motion. This is unsuitable when assessing potentially cyclic motion from flying fauna.

This section explores the application of similarity matrices to assess cyclic motion. Firstly, synthetic cyclic data is used to generate similarity matrices to display the visual spatial relationship. This method is then applied to real flying fauna data.

6.4.2 Generating Similarity Matrices from Synthetic Data

To get a better understanding of how similarity matrices visually represent cyclic data, a number of synthetic 1-d data sequences were generated. These 1-d data sequences are graphically represented in the top rows of Figure 6.10(a-l). The horizontal axis represents time, where each pixel is a time increment. The vertical axis represents the positive value for the data sequence at the specified pixel time increment. Using (Equation 6.2), with the threshold value k = 0.01, and O representing the terms of the data sequence, the similarity matrices for each 1-d sequence were generated (bottom rows of Figure 6.10(a-l)).

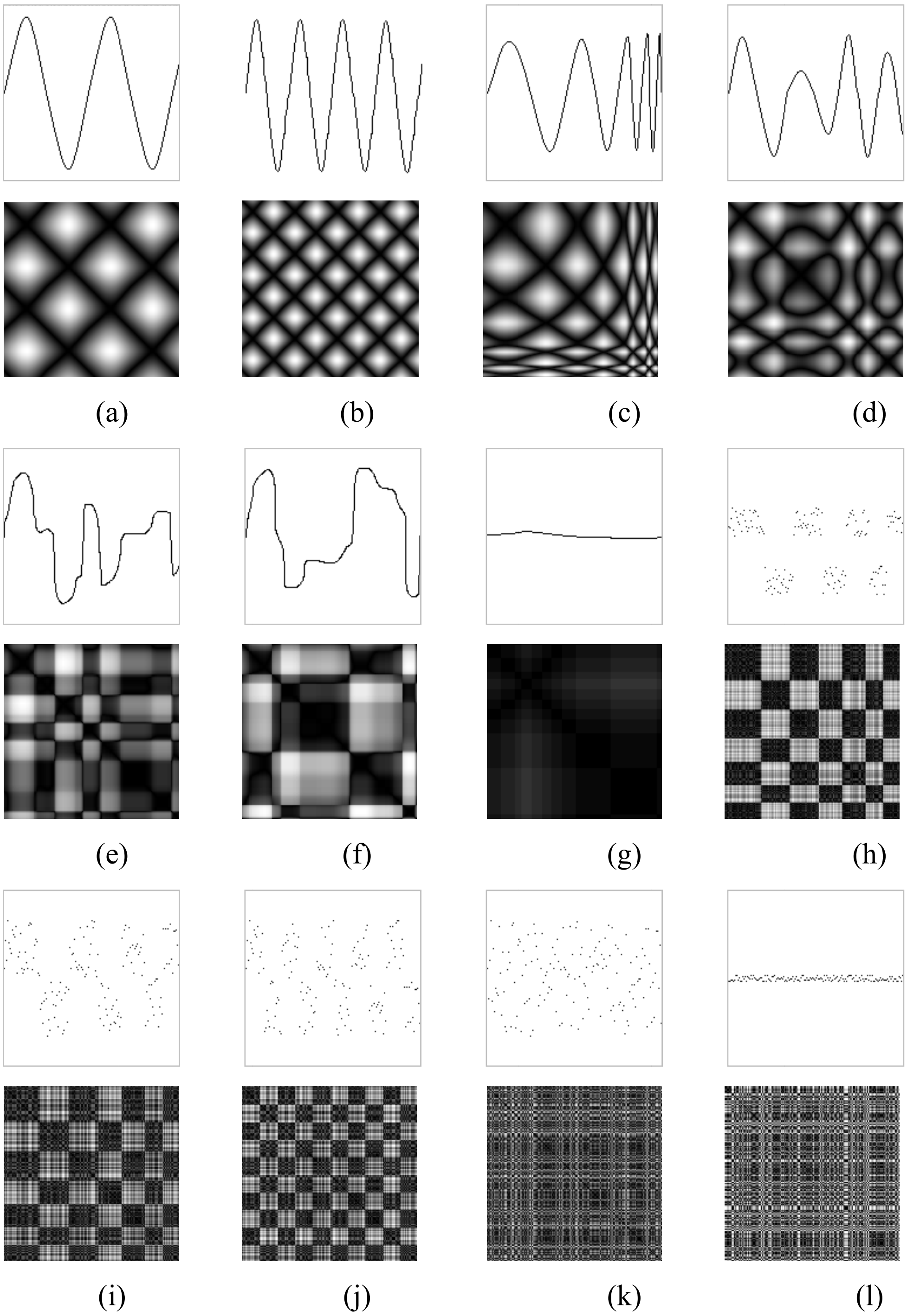


Figure 6.10 A series of 1-d data sequences and similarity matrices. (a, b) periodic sinusoidal. (c) A sinusoidal with increasing frequency. (d) A sinusoidal with constant frequency but varying amplitude. (e, f) Data that oscillates around the middle pixel row, but with no obvious periodicity. (g) Non-cyclic motion. (h, i, j) Randomly generated points to fit periodic and cyclic square waves. (k, l) Randomly generated points. Horizontal axis represents time of 1-pixel intervals. Vertical axis represents value of sequence at specific time interval. All matrices are 150x150 pixels in size

There is a discernable spatial relationship between the periodic and cyclic simulated data, contrasting from the randomly generated noise in Figure 6.10. The 1-d data that is either periodic or cyclic produce similarity matrices that have discernable edges. Even with the 1-d data series generated from periodic or cyclic random points (e.g. Figure 6.10 (i)) edges can still be observed.

6.4.3 Generating Similarity Matrices from Real Flying Bird Data

Clips of flying fauna were used to generate similarity matrices. Fauna included: a bat, Harris Hawk *Parabuteo unicinctus*, Golden Plover *Pluvialis apricaria* (captured using a cooled thermal imager connected to a digital frame grabber) and Rook *Corvus frugilegus* (captured using a digital video camera).

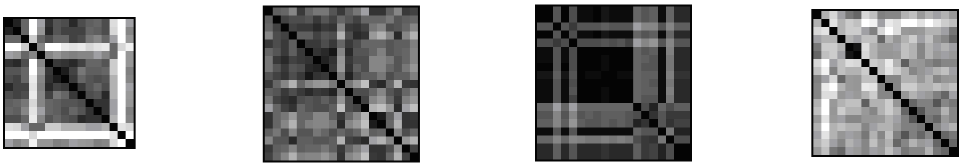
Each image frame was converted to 256 greyscale level images. To reduce the effects of spurious pixel noise, each frame was spatially convoluted with a Gaussian kernel (3x3 kernel, standard deviation=1).

A running average adaptive model was used to segment the bat and Harris Hawk targets from the video background (Chapter 5, Section 5.3.2). A fixed threshold was used (T=18 greyscale values). The segmented images were visually inspected, and any blobs marked up that did not belong to the targets were removed. A total of 16 frames were generated for the bat target, and 19 frames for the Harris Hawk target. The Golden Plover and Rook were hand-segmented frame-by-frame from the video clips, using Microsoft Paint. A total of 19 frames were generated for the Golden Plover target and 18 frames for the Rook target. All of the fauna flew in a uniform direction across the camera's field of view apart from the Rook. The Rook changed direction of flight and its body positioning during its flight across the viewshed.

Once segmented, the flying fauna targets were aligned by their centre of gravity. Each targets similarity matrix was generated using (Equation 6.2).

6.4.4 Results for Flying Bird Data

The resulting similarity matrices for the flying fauna are shown in Figure 6.11. The Golden Plover similarity matrix shows a more rapid wing beat compared to the bat. This can be seen with the grid-like structure within the matrix. The Harris Hawk similarity matrix shows a flap, followed by a soaring period, followed by a flap. The poor definition in the first flap in the matrix is due to poor segmentation in a couple of the frames. The Rook similarity matrix has some texturing, but it is difficult to ascertain cyclic or periodic motion within the matrix.



(a) (b) (c) (d)

Figure 6.11 Cyclic motion for flying fauna. (a) bat, (b) Golden Plover, (c) Harris Hawk, (d) Rook. All images have been enlarged by 400%

6.4.5 Discussion for Representing Cyclic Motion

As with the synthetic data, the real flying fauna data produced cyclic similarity matrices. In addition, each fauna has produced spatially different similarity matrices. Apart from the Rook, the other flying fauna had recognisable cycles occurring, corresponding to wing oscillations. The variable appearance of the Rook similarity matrix could be attributed to continual changes in body position as it flew.

6.4.6 Conclusion for Representing Cyclic Motion

The similarity matrices produced for the flying fauna suggest that area-based differencing may be used as one part of a method to identify species groups.

6.5 Discussion

The feature analysis method for detecting periodicity, based on Niyogi and Adelson’s (1994) method was not successful for detecting flapping motion. Although periodicity could be detected in the XT ankle section, only the white marker could highlight the flapping motion, rendering this method unsuitable for monitoring flying fauna.

Area-based periodicity detection, based on Cutler and Davies' (2000) use of similarity matrices successfully classified periodic motion from both the varying intensity dot and turbine examples. A relatively straightforward system can be implemented to extract the key frequency at which periodicity occurs.

Further exploration of area-based periodicity detection shows potential application in detecting cyclic motion in addition to periodic motion. Spatial inspection of the generated inter-frame similarity matrices identifies differences according to fauna.

6.6 Conclusion

The area-based periodicity detection method using inter-frame similarity matrices has proven to be successful at detecting periodic motion in test data.

However, birds do not always fly with periodicity. Flapping variation can depend on types of flight, time length during wing oscillation and time length between wing oscillations. If target motion changes are used as a tracking method, it is important to consider cyclic oscillations in addition to periodicity. It has been shown that cyclic motion, as well as periodic motion, can be represented in similarity matrices. A pattern can be observed in the matrix when an object exhibits cyclic or periodic motion, identified by the well-defined spatial edges. This is in contrast to when only noise is present.

Initial results have shown that different flying fauna produce different similarity matrices. These differences may possibly be used for identifying fauna through automated means. Approaches to classifying flying fauna species based on wing oscillations are explored in Chapter 7.

Chapter 7: Identifying species groups using similarity matrices

7.1 Introduction

When using a thermal imaging camera to view flying fauna, it can be difficult to identify the species under surveillance, with little or no shape information available. With prior knowledge of bird species present at a site, it is easier to categorise these unidentified flying fauna.

Research reported in Chapter 6 suggested that different bird species have spatially varying inter-frame self-similarity matrices. Tracking areas of interest (the bird target) and computing the corresponding similarity matrix is a favourable approach for representing faunal motion as it is robust with respect to target distance, and there is no need to track specific limb motion (Cutler and Davis 2000).

As reviewed in Chapter 2 spatial differences within similarity matrices have been used in visual applications to distinguish between targets. The aim of this chapter was to determine how spatial patterns in similarity matrices could classify different bird species. This was achieved by:

- using identified flying bird video clips to generate similarity matrices for visual assessment;
- conducting an observer-based perception trial; and
- investigating template matching and supervised learning using a neural network as an approach for species classification.

7.2 Similarity Matrices of Birds

7.2.1 Relationships between Different Targets and Their Similarity Matrices

Cutler and Davis (2000) use such matrices to classify objects moving with periodicity as person, dog or everything else. BenAbdelkadar *et al*. (2004) use the spatial variances within a similarity matrix to classify people based on their walking style. There is strong evidence that motion dependent movement can be used for the classification of birds in flight, something that (based on findings from literature searches), has yet to have been attempted. The aim of this section is to generate similarity matrices from identified bird video clips for visual assessment and for use in classification in the following sections. A brief discussion of the strengths of this approach and difficulties encountered is also provided.

7.2.2 Method for Generating Bird Similarity Matrices

Sample clips of bird flights were obtained from nocturnal bird surveillance video gathered from past RPS bird surveys. The surveillance video was originally gathered from a thermal imager, with the analogue video output connected to a digital frame grabber. Video clips lasting longer than one second were generated containing flying birds. This was to increase the likelihood of getting enough bird wing oscillations for the matrices. Although this significantly reduced the number of video clips available, it was felt that having sufficient wing oscillations would aid the initial assessment of this approach for assessment. The birds in the clips had either been identified whilst the surveyor was in the field, or by the surveyor from the video footage after the survey had been concluded.

To generate the matrices, the birds were separated from the background in the video clips using a running average with a fixed threshold value of 18 greyscale levels, based on the value used in Chapter 5. As many of the clips had a bird in the initial frame, using the first frame to initialise the running average model would assume the bird was part of the background model. To overcome this, a temporal median frame, generated from the first 20 frames of the video clip was used to initialise the running average background model (Monteiro *et al*. 2008). The similarity matrices were generated using the method described in Chapter 6. This process was semi-automated by using mean-shift tracking (Comaniciu *et al.* 2000). Once a bird had been segmented and binarised, it was tracked and aligned by its centre of gravity, reducing the need to inspect each frame for falsely segmented objects.

7.2.3 Matrix Generation

The large gull (Herring Gull *Larus argentatus*, Great Black-Backed Gull *Larus fuscus* or Lesser Black-Backed Gull *Larus marinus*), small gull (Common Gull *Larus canus* or Black-Headed Gull *Larus ridibundus*) and Little Egret generated large matrices consisting of at least 50 frames. When a bird is actively flying through wing oscillations, their wing-beat frequencies are expected to be in the order of a few beats per second. As the changes in bird shape are used to generate the matrices, changes in relative shape due to the bird changing flight direction or orientation to camera may create a distinct difference between previous frames once collated into a matrix. In addition a number of frames are required to capture a minimum of two wing oscillations for a similarity matrix as suggested by Cutler and Davis (2000). Careful selection of frame numbers to form a sample will likely include constant bird heading and orientation for the duration of the sample and at least two wing oscillations. 20 frames (and values close to this) meet these criteria based on a frame-capture rate of 25-30 frames per second. These matrices were sub-sampled into a number of 20x20 matrices to generate more samples for testing. The samples were extracted along the top left to bottom right diagonal of a given matrix to ensure that the matrices obtained were representative of inter-frame differencing. This was the equivalent of splitting the video sequence up into smaller time periods and then generating separate similarity matrices. To enhance the textures within the matrices, contrast equalisation based on histograms with 0.5% saturation cut off was used. As mentioned in the previous chapter, contrast equalisation enhances the distribution of intensities across the matrix automatically, and replaces the approach previously used in Chapter 6.

Figure 7.1 to Figure 7.5 shows some of the similarity matrices generated (whole and sub sampled) from a number of species with contrast equalisation applied.

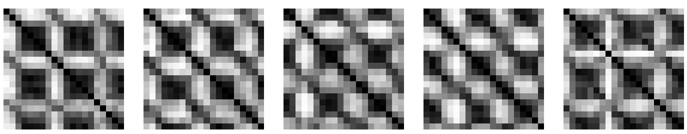


Figure 7.1 Sample images of large gulls (from five video clips)

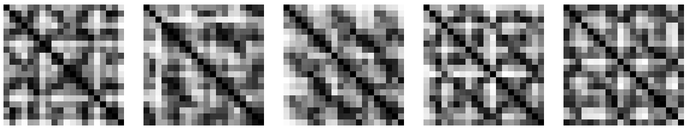


Figure 7.2 Sample images of large gulls (from two video clips)

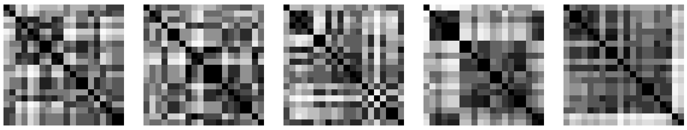


Figure 7.3 Sample images of small gulls (from three clips)

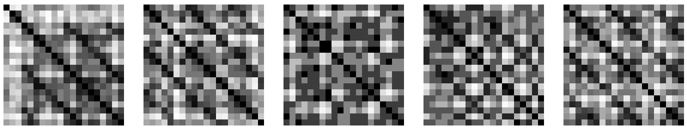


Figure 7.4 Sample images of Little Egrets (from two video clips)

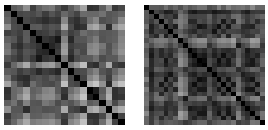


Figure 7.5 Sample images of Golden Plover *Pluvialis apricaria* (from two video clips)

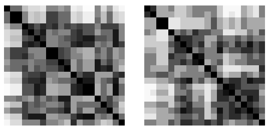


Figure 7.6 Sample images of thrushes (identified as Redwing *Turdus iliacus* by call - from two video clips)

Larger on-screen bird targets proved to be the most successful for generating similarity matrices. The larger the target was (pixel size) the less susceptible it was to inaccurate segmentation from the background. A limitation encountered whilst processing the video clips was artefact aliasing due to the video capture technique. The effect of the artefact aliasing caused two consecutive positions of the bird target to overlap in one frame (Figure 7.7). A progressive-scan frame grabber should not suffer from artefact aliasing.

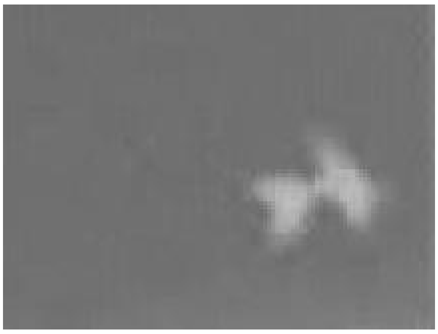


Figure 7.7 Example of Golden Plover and artefact caused by aliasing

One instance of interest is where large gulls have produced one of two types of similarity matrix (Figure 7.1 and Figure 7.2). One possible explanation is that the variation is caused by small amounts of aliasing in the video clip. Another possibility is that one type of similarity clip is from either a Herring Gull or a Lesser-Black Backed Gull (which are similarity sized and hence have very similar flapping patterns) and the other from a Great-Black Backed Gull (a larger gull with a slower flapping pattern compared to the other large gulls). Also the two thrush similarity matrices varied from each other (Figure 7.6). This also could be due either to aliasing, or that the two video samples are not long enough to cover the varied flap patterns a thrush can exhibit.

7.2.4 Discussion for Matrix Generation

Overall, using successfully generated similarity matrices, some of the bird and families are visually similar to each other, such as the gulls and Little Egret, but different when compared against other birds. The thrush did not produce comparable matrices based on the two video samples, and additional video clips are needed to see whether there are any general similarities. Artefact aliasing is due to a hardware problem and is not related to the method of generating similarity matrices. More accurate target segmentation will likely increase the number of smaller-pixel targets that produce useful matrices. It is likely that there will be a size limitation where bird shape does not vary enough to produce differences within a similarity matrix.

7.2.5 Conclusion for Generated Matrices

This work suggests that similarity matrices for birds in flight are visually similar for family species. The extent of this visual similarity is investigated in the next section. Further work into improving the sensitivity of bird segmentation from scene background is recommended to expand similarity matrix generation to pixel-related small targets.

7.3 Perception Test to Assess Comparability of Bird Similarity Matrices

7.3.1 Visually Assessing Matrix Similarity

Perception tests can be used to quantify how similar an image is to other samples. This section uses a perception test carried out with volunteers, to see whether a human can identify different bird species based on comparing different similarity matrices. This approach was chosen as it provided an indicative response as to whether bird species could be grouped by similarity matrices.

7.3.2 Method for Perception Test

Using similarity matrix samples from Figure 7.1 to Figure 7.4, a total of 20 images (5 per group) were used to create a perception test. One image from each group was randomly selected as keys, whilst the remaining 16 images were randomly shuffled. The key images and test images were presented as printed hand out (Appendix F). Each volunteer was presented with the hand out and was asked to look at each test image, compare the test image to the key images, and decide which key it most closely resembled.

7.3.3 Results of Perception Test

A total of six volunteers carried out the test. The majority of the volunteers correctly identified over half of the matrices (mean = 10.17, standard deviation = 2.03). Individual identification rates are shown in Table 7.1.

Volunteer	Number of Similarity Matrices Identified (16 total)
1	6
2	10
3	11
4	12
5	12
6	10

Table 7.1 Number of correctly identified matrices for each volunteer

The results for all of the volunteers were combined and used to create a confusion matrix (Table 7.2). There were some misclassifications for all of the sample groups. Overall the majority of images were correctly classified.

		Predicted			
		Large Gulls (Figure 7.1)	Large Gulls (Figure 7.2)	Small Gulls (Figure 7.3)	Little Egrets (Figure 7.4)
Actual	Large Gulls (Figure 7.1)	22	2	0	0
	Large Gulls (Figure 7.2)	2	11	4	7
	Small Gulls (Figure 7.3)	2	0	17	5
	Little Egrets (Figure 7.4)	0	10	3	11

Table 7.2 Confusion matrix for combined volunteer responses

7.3.4 Discussion of Perception Test

Overall the majority of the test images were correctly classified. The majority of the volunteers were able to group most of the test images using the provided keys. It is apparent that volunteer 1 misinterpreted a number of the images, although the cause of this is unknown. Volunteer 1 was the only person to misclassify all of the Little Egret test images, classifying them all as Large Gulls.

7.3.5 Conclusion of Perception Test

The results from the perception test support the chapter proposition that motion dependent movement can be used for the classification of birds in flight through the use of inter-frame similarity matrices.

7.4 Classifying Birds through Cross-Correlation

7.4.1 Introduction to Correlation

The examples presented in Figure 7.2 to Figure 7.5 highlight the fact that certain textures within the matrices repeat. These repeating patterns can be regular such as grid style patterns (Golden Plover and large gulls), diamond style patterns (such as Little Egret *Egretta garzetta*), or merely have repeating patches within the matrix (such as small gulls). Identifying repeating features within other similarity matrices for the same species group may provide a way of contrasting them from other flying fauna. A recognised approach for finding a specific spatial feature within an image is through cross-correlation (template matching). This approach was used by BenAbdelkader *et al.* (2004) to classify a person's gait based on their similarity matrix and is hence being trialled to see whether it can be used to classify different bird species similarity matrices.

Using a simple, 1-dimensional example, assume a pattern is required to be located from the following series [0 0 1 2 1 0 0 1 0 0 2 0 0 1 2 1 0 0] (Table 7.3). To find out how often the pattern [1 2 1] occurs in the series, this kernel is scanned across the 1-dimensional vector. Each corresponding term is multiplied by the terms in the kernel, and the products are summed. Once the correlation is complete, peak values in the correlation result indicate where the kernel had the highest correlation in the series (Table 7.3).

Series and Kernel Position	Progress of Correlation
0 0 1 2 1 0 0 1 0 0 2 0 0 1 2 1	1 0 0 0 0 0 0 0 0 0 0 0 0 0
[1 2 1]	
0 0 1 2 1 0 0 1 0 0 2 0 0 1 2 1	1 4 0 0 0 0 0 0 0 0 0 0 0 0
[1 2 1]	
0 0 1 2 1 0 0 1 0 0 2 0 0 1 2 1	1 4 6 0 0 0 0 0 0 0 0 0 0 0
[1 2 1]	
0 0 1 2 1 0 0 1 0 0 2 0 0 1 2 1	1 4 6 4 0 0 0 0 0 0 0 0 0 0
[1 2 1]	
...	...
0 0 1 2 1 0 0 1 0 0 2 0 0 1 2 1	1 4 6 4 1 1 2 1 2 4 2 1 4 6
[1 2 1]	

Table 7.3 Using correlation to find a specific patter. Left: 1-d series with kernel position. Right: Progressive result of correlation. Bottom row shows the completed correlation, with peak values shaded

Using this approach for 2-dimensional images a feature being sought after within the image can be created into a search kernel (the template). The kernel is scanned across the image, with the correlation result showing where the best matches for the kernel are located on the image. Rather than having a variable peak number, the correlated value is normalised to a range between –1 (negative correlation) and 1. The result is a single value for the central pixel under the kernel cover. The nearer the pixel value is to 1, the better the correlation (match to the template kernel). Values nearer to -1 suggest negative correlation, whereas values approaching 0 suggest no correlation.

7.4.2 Method for Target Classification using Cross-Correlation

The similarity matrices used are identical to those generated in Chapter 6, with the matrices shown in Figure 7.8. Using the Golden Plover similarity matrix from Figure 7.8(b) as a base, a section of the matrix encompassing a cycle was used to create the template (Figure 7.9). At the time of this trial, a single matrix for each species was available and used, with an additional Golden Plover matrix generated from a different event. As the additional Golden Plover event was captured at 29.97 frames per second (rather than 25 frames per second), the resulting similarity matrix was scaled down by 20%. ImageJ (NIH 2008) with the template matching plug-in used to perform the correlation (O'Dell 2005).

Each similarity matrix in turn was correlated with the template. All correlation points with a value above 0.5 were counted as template matches. This value was chosen as any peaks detected would show some degree of correlation, and would reduce the likelihood of multiple peaks for a single pattern.

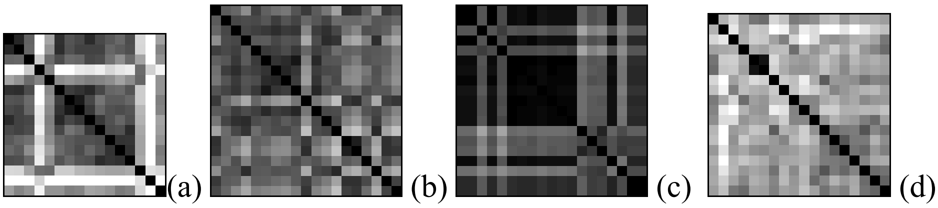


Figure 7.8 Similarity matrices from flying fauna. (a) bat; (b) Golden Plover *Pluvialis apricaria*; (c) Harris Hawk *Parabuteo unicinctus* and (d) Rook *Corvus frugilegus*

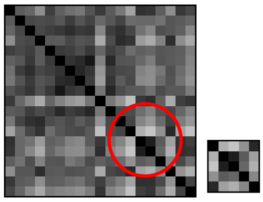


Figure 7.9 The Golden Plover similarity matrix used to create the template, and the template based on a random feature selected from the matrix

Sub-sampled large gull and Little Egret matrices generated in Section 7.2 were used to carry out an additional trial. A kernel was selected from one of the large gull matrices as shown in Figure 7.10. As with the Golden Plover instance used above, the kernel was passed over large gull and Little Egret matrices. Ten large gull sub-sampled matrices (from the original five large similarity matrices) and ten Little Egret sub-sampled matrices (from the original two large similarity matrices) were used.

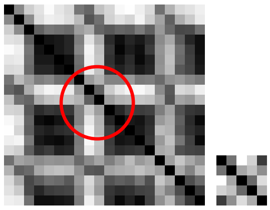


Figure 7.10 Large gull matrix and associated, randomly selected feature-based kernel

7.4.3 Results for Target Classification using Cross-Correlation

All correlation peaks were tallied for each similarity matrix (Table 7.4). A peak is defined as any pixel at or over the correlation value of 0.5 and any adjoining neighbouring pixels with this criterion.

Flying Fauna (Correlated with Kernel)	Number of Peaks with Correlation Value >0.5
Original Golden Plover	11
Bat	3
Additional Golden Plover	6
Harris Hawk	2
Rook	4

Table 7.4 Summary of the number of correlation peaks found using the Golden Plover kernel in Figure 7.9

For the large gull and Little Egret data, the number of peaks with correlation values above 0.5 and adjoining neighbouring pixels are shown in Table 7.5.

Matrix Sample Number	1	2	3	4	5	6	7	8	9	10
Large gull	6	9	3	6	6	5	6	4	5	3
Little Egret	4	4	9	11	9	7	10	12	12	11

Table 7.5 Summary of the number of correlation peaks found using the large gull kernel in Figure 7.10

7.4.4 Discussion for Target Classification using Cross-Correlation

The initial trial for differentiating Golden Plover from the other flying fauna appeared to be successful. The two similarity matrices with the highest number of correlation peaks >0.5 were the original Golden Plover matrix and the additional Golden Plover matrix.

The additional trial using sub-sampled large gull and Little Egret matrices were not so successful. The majority of the Little Egret matrices produced more peaks when correlated with the large gull kernel template compared to the large gull matrices. The Little Egret matrices had a large number of light pixels (which have a high value) compared to dark pixels (which have a low value). The Large gull matrices had a large number of dark pixels to white pixels. It is possible that the overall high content of lighter pixels in the Little Egret matrices would produce a large number of correlation peaks, falsely suggesting good matches with the search kernel.

7.4.5 Conclusion for Target Classification using Cross-Correlation

A person's gait may vary slightly in scale, but the structure is similar (BenAbdelkader *et al.* 2003). The features within the similarity matrices for birds can vary dramatically from species to species. Although initial results using the Golden Plover were promising, the use of the large gull and Little Egret matrices highlighted a limitation using correlation. The work in this section suggests that template matching is not likely to be a suitable tool for bird species classification based on similarity matrices.

7.5 Classifying Species through Supervised Learning

7.5.1 Introduction to Supervised Learning

In this section, feed-forward neural networks are used to classify two groups of two bird species groups. The first group consisted of large gulls mainly containing Herring Gulls with some Great Black-Backed Gulls, and Little Egret *Egretta garzetta*. The second group consisted of large gulls and Gannets *Morus bassanus*. A feed-forward neural network was chosen for the distinguishing between the bird samples as it was a readily available tool that seeks patterns within data automatically. Neural networks are popular for target classification as they are not dependent on prior problem information and feed-forward neural networks are commonly used in classification tasks (Jain *et al*. 2000). Pre-processing of the similarity matrices is used to reduce the number of inputs required for the neural network. Singular Value Decomposition (SVD) is used to decompose the similarity matrices into factors that are sorted by magnitude. This approach was chosen as it sorts decompositions by factor, and removes initialisation problems in looking for specific textures or cycles within a similarity matrix are avoided. Method for Classifying Bird Species using Neural Networks

Two sets of input data in each group were separately used in training and testing the neural networks. The video sequences were captured at 30 frames per second, and the majority of bird events lasted several seconds in duration. Only video clips where the birds were observed to oscillate their wings with no clearly observable soaring were used. The order of the matrices was randomised, so consecutive matrices from each group were unlikely to come from the same original similarity matrix. To reduce the number of input vectors for the neural network, SVD was applied to all of the matrices, producing a 20-element array for each matrix. For the first group consisting of large gull and Little Egret similarity matrices, a total of 30 large gull and 16 Little Egret sub-sampled matrices were used. For the second group consisting of large gull and Gannet similarity matrices, a total of 114 20x20 large gull and 114 Gannet matrices were generated by sub-sampling the original 40 matrices (Figure 7.11).

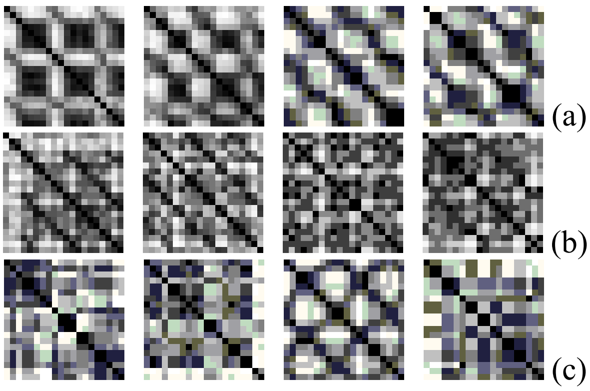


Figure 7.11 Some of the sub-sampled similarity matrices. (a) large gull. (b) Little Egret. (c) Gannet

The neural network used for both classification groups consisted of a two-layer, feed-forward neural network with tan-sigmoid transfer functions for both layers. The network was implemented from the MATLAB 7.0 neural network toolbox. The input and hidden layer each consisted of 20 neurons for each of the 20 factor values outputted from the SVD transform (Figure 7.12). The neural network toolbox suggested network set up of a scaled conjugate gradient was used for training. The number of layers used could have been increased, although it is doubted that would have improved the level of classification achieved.

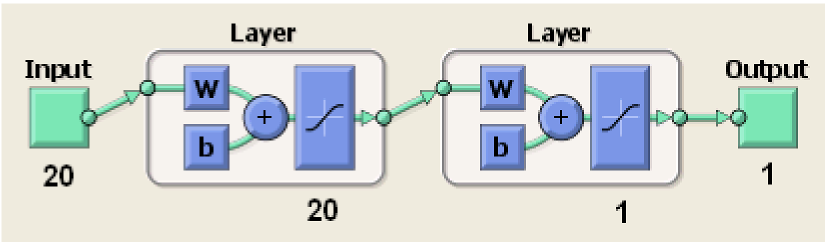


Figure 7.12 Two-layer feed-forward neural network

For the first group 30 samples were randomly selected to train the system, 6 samples used to validate the system and 6 samples to test the system. Target vectors were either 0 for large gulls or 1 for Little Egret. For the second group 160 samples were randomly selected to train the system, 34 samples used to validate the system, and 34 samples used to test the system. Target vectors were either 0 for large gulls or 1 for Gannets. The number of samples used to train, validate and test the system could be varied. Increasing the number of samples used to train the system may improve performance, but at a cost of samples available for network validation and testing. In addition neuron weightings could also be adjusted. As the matrices are reduced to 20 values ordered by factor, adjusting the weighting based on the first few factors may improve the performance of the neural network, although this would need investigation.

7.5.2 Results for Classifying Bird Species using Neural Networks

First Group (Large Gulls and Little Egrets)

The training data used for supervised learning resulted in 100% correct classification of large gulls and 100% correct classification of Little Egrets. Only a single misclassification of a Little Egret sample occurred during the validation stage. Combining all the samples that were used during the learning, verification and validation stages, 100% (30) large gulls and 94% (15) Little Egret samples were correctly classified The confusion matrix for the combined results is shown in Table 7.6.

		Predicted	
		Large gull	Little Egret
Actual	Large gull	30	0
	Little Egret	1	15

Table 7.6 Confusion matrix for combined neural network output for large gull and Little Egret

Second Group (Large Gulls and Gannets)

The training data used for supervised learning resulted in 60% correct classification of large gulls and 68% correct classification of Gannets. The data used for validation produced 68% correct classification of large gulls and 53% accurate classification of Gannets. The remaining data used for testing the neural network resulted in 54% correct classification of large gulls and 75% correct classification of Gannets. Combining all the samples that were used during the learning, verification and validation stages, 74% (84) large gulls and 52% (59) Gannet samples were correctly classified The confusion matrix for the combined results is shown in Table 7.7.

		Predicted	
		Large gull	Gannet
Actual	Large gull	84	55
	Gannet	30	59

Table 7.7 Confusion matrix for combined neural network output for large gull and Gannet

7.5.3 Discussion for Classifying Bird Species using Neural Networks

The initial trial based on the limited number of input images for the matrix proved promising. Singular value decomposition reduced potentially 400 elements (20 by 20 matrix) to 20 values, whilst still being representative of the matrix. This approach was chosen as it offered a way of reducing the number of input neurons, and hence the complexity of the neural network in addition to sorting values by magnitude. Similar patterns occurring within different similarity matrices should have similar singular value decomposition outputs (using matrices of the same size). This was important as unlike the cross-correlation approach tried in Section 7.3 no initialisation or feature searching was required prior to classification, simplifying the process.

The use of the feed-forward neural network from the MATLAB toolkit was also beneficial, allowing rapid implementation of the classifier. The first classification group using large gulls and Little Egret produced positive results based on the small sample set. There were a number of misclassifications in the second group using large gulls and Gannets and it is believed that this may have been caused by some similarity in flight style of both large gulls and Gannets. Also varying wind strengths whilst the video samples were collected may have had an impact on bird flight styles.

7.5.4 Conclusion for Classifying Bird Species using Neural Networks

This section has presented a method for automating the classification of two bird species based on similarity matrices, with promising initial results, without requiring prior normalisation or initialisation of the matrices prior to use.

7.6 Discussion

This chapter has explored how bird flight characteristics can be differentiated based on similarity matrices, and investigated approaches that may classify between bird species.

It is evident that some bird species groups have comparable similarity matrices, which can potentially be a powerful identification tool. This view has been strengthened with results from the perception test. A limitation, based on the target segmentation approach used in this chapter, currently reduces usable video clips to those containing larger birds (based on pixel size).

Using template matching as an approach for differentiating between different flying fauna similarity matrices was found to be unsuccessful when used to differentiate between large gull and Little Egret. As the large gull and Little Egret matrices vary significantly from each other and the level of light, high value pixels is distributed more frequently in the Little Egret matrices, this may have caused high correlation peak values. Another limitation with this approach is the need to initialise the cross-correlation by selecting a search kernel. With similarity matrices that do not have cycles to extract (e.g. Little Egret), this is an added complication.

The use of a neural network classifier was more successful. Singular value decomposition removed the need of initialisation by reducing the similarity matrices down to factors sorted by magnitude, irrelevant of what cycle phase the similarity matrix commenced with. The singular value decomposition values also reduced the number of input vectors required by the forward-feed neural network from 400 (i.e. 20 by 20 matrix) to 20. For the first group, the neural network through all phases only misclassified a single Little Egret sample. In the second group the neural network through all phases successfully classified 63% of the large gull and Gannet matrices. There were a number of matrices that were misclassified in the second group. It is believed this is due to Gannet wing oscillations adjusting according to wind speed more readily (Snow and Perrins 1998), producing varied results.

7.7 Conclusion

This chapter has shown that bird species uniqueness based on flying motion can be represented in similarity matrices. Although these similarity matrices may not be used to classify all bird species, an automated system that identifies some of the birds could speed up analysis time, leaving more complex cases to experienced ornithologists.

Some limitations were encountered whilst generating the similarity matrices. Artefact aliasing was due to how the video was gathered, and is not related to the method used to produce the similarity matrices. Better bird segmentation could extend more successful similarity matrix generation to smaller (pixel related) bird targets.

This chapter has presented an approach that can differentiate between two bird species. Singular value decomposition provided a straightforward approach to reduce a similarity matrix down to a number of ordered inputs, removing the need for pre-initialisation. A feed-forward neural network facilitated classification by using these inputs based on the data of large gulls and Gannets.

Further work is recommended in generating additional similarity matrices for different bird species whilst in flight. These matrices can be used to further examine how matrices relate to bird species, and more thoroughly test a classification system. Addressing the problems encountered with poor segmentation and artefact aliasing, along with the effects of varying wind on certain bird species will assist this further work.

Chapter 8: Conclusions and Further Work

8.1 Conclusions and Contributions to Knowledge

The overall aim of this project was to improve the efficiency of nocturnal bird surveillance using night vision equipment. This has been achieved through the following key contributions to knowledge.

Development of a selection method to aid the use of night vision equipment in nocturnal bird surveillance

Thermal imagers and image intensifiers operate in fundamentally different ways. Image intensifiers amplify available light photons and are dependent on a level of ambient scene lighting. Thermal imagers detect heat emitted from a scene and are completely light independent. These different properties will affect which device is chosen for nocturnal bird surveys.

As image intensifiers amply available light photons, shading and plumage detail of birds can be observed. Hence an image intensifier is necessary where the identification of birds down to species level is required. Birds emit measurably greater quantities of heat compared to their surroundings. Hence a surveyor can use a thermal imager to rapidly detect the number of birds present in an area, and identify them to species family.

An infrared lamp greatly improves the performance of an image intensifier, no reason was found for not using one during nocturnal bird surveys.

Where monitoring airspace for bird activity is necessary, it is far quicker and easier to detect birds flying against the sky with a thermal imager compared to an image intensifier. A relatively hot bird target against a relatively cold sky produces a far greater contrast compared to a dark sky with a mottled-shaded bird. Using an infrared lamp did not improve target detection. In these circumstances it is far more appropriate to use a thermal imager.

The image intensifier could not detect targets beyond visibility levels in fog, unlike the thermal imager, which was capable of detecting imitation bird targets further than visibility offered in fog.

Overall, a thermal imager out performs an image intensifier in detecting bird targets, whilst an image intensifier out performs a thermal imager in identifying bird targets to species level.

Creation of methods to improve the efficiency and accuracy of the analysis of nocturnal thermal imager video

Size and flight speed (relative to the screen) have been determined to affect a surveyors ability to detect flying targets. By reducing the speed at which bird surveillance video is reviewed, the detection rate of flying fauna from video samples significantly increases. This improves the accuracy of nocturnal bird survey video, but takes a far longer time to review the video. Also, as it is a human-based process, it is susceptible to boredom, fatigue and error.

Motion detection can be automated using background subtraction and cumulative image differencing techniques. Both approaches generally outperform a human surveyor for detecting motion and can be run without surveyor involvement during video processing. This also reduces the amount of time a human observer requires to review video of inactivity.

Nocturnal bird surveys in addition to diurnal surveys are important as birds are active at night as well as during the day, exhibiting varying behaviour. The sponsoring company RPS uses the experience obtained from the field trial, coupled with the first contribution to knowledge in determining how to plan a nocturnal bird survey. Information on the strengths and limitations of the night vision equipment is also used increasingly being used by the company's bat surveyors. Once the video has been collected, based on whether there is large amounts of cloud movement, the motion detection approaches are used on the collected survey video to speed up analysis.

Creation of a method to identify bird species from wing oscillations using inter-frame similarity matrices

The distinct locomotion of flying birds is used by experienced ornithologists to identify species. Transforming a number of frames from a video sequence of a flying bird into a single similarity matrix is a convenient way to not only identify periodic motion but to use the matrix for bird species classification. Applying singular value decomposition offers a convenient way of reducing a similarity matrix down to its key factors and sorts these factors by magnitude, alleviating the need to initialise or normalise the matrix prior to classification. A feed-forward neural network can then be used to classify bird species based on these key factors.

8.2 Restatement of Theses

The aim of this research project was to improve the accuracy, efficiency and application of nocturnal bird surveys.

The first thesis statement was that a framework could be developed for the systematic use of infrared thermal imaging and image intensifying in nocturnal bird surveillance. This was demonstrated through summarising information gathered from field trials and surveyor interviews.

The second thesis statement was that the oscillatory flying motion of birds could be used to classify different species in an automated computer vision system. This was demonstrated using a technique based on inter-frame similarity matrices and a neural network classifier.

8.3 Further Work

With respect to this project, the following three areas are suggested for further work.

8.3.1 Assessing Thermal Imager and Image Intensifier Detection and Identification Ranges against the Sky

Chapter 3 has provided guidance for night vision equipment usage with respect to nocturnal bird surveillance. A general overview of equipment range was determined through field trials and the experience of the surveyors was used to understand other aspects of the equipment. One area the interviews highlighted as being a major strength of the thermal imager and a great limitation of the image intensifier was the ability to observe bird targets against the sky. This has been identified within the interviews, but there is no quantitative data available to understand the effective operational range of the image intensifier (or the thermal imager) in these circumstances. It is recommended that trials to assess the night vision equipment against the sky are carried out.

8.3.2 Blocking Rotating Wind Turbine Blades

There is growing interest to monitor bird and wind turbine interaction. As identified in Chapter 2 radar and acoustic-based approaches are unable to provide details on birds within turbine blade airspace. As identified in Chapter 3 image intensifiers perform poorly at detecting birds against the sky. This leaves thermal imagers as the most suitable candidate for monitoring bird and turbine interactions. It would be advantageous to be able to adaptively mask the continual rotation of the turbine blades, which currently will trigger most motion detection techniques. It is recommended that further, detailed research into turbine suppression approaches is attempted.

8.3.3 Focussed Bird Classification

The work presented in Chapter 7 presented a promising approach to identify bird species groups based on wing beat oscillations. Provided that the artefact aliasing issue is resolved using an appropriate digital frame grabber, additional work to resolve poor segmentation is recommended. Also to improve the confidence of bird species classification, targeted video data collection of known species is recommended to;

- identify which bird species are identifiable using the approach outlined in Chapter 7; and
- extend the testing of the application with a larger dataset.

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Appendix A: Journal and Conference Papers

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Taylor & Francis
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RESEARCH CONTRIBUTION

Wind farm and fauna interaction: detecting bird and bat wing beats through cyclic motion analysis

Ljubica Lazarevic[a]*, David Harrison[a], Darren Southee[a], Max Wade[b] and John Osmond[a]

[a]*School of Engineering and Design, Brunel University, Uxbridge, England, UK;* [b]*RPS Ecology, St Ives, England, UK*

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Recent Government announcements have implied that wind power will play a major part in providing energy for the UK (BBC 2007). However, there is much concern that wind farms can have a significant impact on flying fauna (bats and birds) using the area, particularly at night. As part of an Environmental Impact Assessment, thorough appropriate surveys are necessary for quantifying and minimising any risk wind farms may cause flying fauna. Manual surveys that are commonly used are not always cost-effective, efficient or practical. Remote systems based on motion detection are increasingly being used to monitor wildlife. Fast-moving airborne targets such as aeroplanes can falsely trigger motion-detection based remote systems. As birds and bats repetitively flap their wings, this oscillating motion can be used to distinguish them from other airborne targets. Time periods between wing oscillations are not always constant, and hence the motion is not periodic. A method to detect cyclic motion based on similarity matrices is proposed, and synthetic and real data are used.

Keywords: windfarms; birds; bats; cyclic motion; wing beat frequency; environmental impact assessment; nocturnal surveys

1. Background

Renewable technologies, such as those using wind power, may help meet the United Nations Environment Programme aims of sustainability (UNEP 2006). As a mature technology, renewable energy from wind is considered as one of the leading tools for tackling carbon emissions. Recently, the British Government has announced its intention to develop and install more wind farms to meet the demand for lower carbon generated energy (BBC 2007). This demand is likely to be met with offshore wind farms, with the UK expected to be the largest generator of offshore wind power worldwide in 2008 (BWEA 2007).

Offshore wind farms are likely to be one of the largest man-made interferences in the seas around Europe (Exo *et al.* 2003). Onshore wind farms also pose problems, with poorly located wind turbines potentially causing collision risks, or harming and reducing habitat (RSPB 2005). Also infrastructure associated with wind farms can have a devastating effect (e.g. Kuvlesky *et al.* 2007).

To try and reduce the unnecessary impacts of structures such as wind farms on birds and bats, Environmental Impact Assessments (EIA), as part of a European Union directive, are required to be conducted during the proposal stage (DCLG 2000). As part of the EIA, natural heritage likely to be affected by a schedule one development (see Town and Country Planning regulations 1999) are identified. Identified natural heritage at risk have to then be assessed for potential impacts. For birds and bats, relevant surveys may be carried out to collect information on area activity, species numbers, area utilisation, etc. This data are then analysed by specialists who can provide the developer with information concerning the risk to the environment (DCLG 2000).

Research shows that many bird species, such as ducks, geese and waders are active at night as well as during the day. Bird groups such as passerines (e.g. Schmaljohann *et al.* 2007), waders (e.g. Gudmundsson 1994), geese (e.g. Alerstam *et al.* 1993) and ducks (e.g. Flock 1973) migrate at night. In addition to migrating and moving to roosts, birds may be engaged in other activities. For example, wader species such as Lapwing *Vanellus vanellus* feed at night to balance their energy budgets (Sheldon *et al.* 2004). Redshanks *Tringa totanus* have been found to forage for food more at night than during the day (Burton and Armitage 2005), and other shorebird species have been observed foraging at night (McNeil and Roberts 1992). As nocturnal behaviour may not always match diurnal behaviour (Gillings *et al.* 2005) nocturnal surveys are vital to supplement information regarding species behaviour at a potential development site.

Bats are also at threat from poorly located wind turbines. A number of causes of bat mortality at wind

*Corresponding author. Email: ljubica.lazarevic@brunel.ac.uk

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turbines have been speculated including migration, high altitude foraging flights, interference with ultrasound and wind turbine wind-shear (Williams 2004, Bets 2007). Bats must be considered as part of an EIA, and appropriate surveys carried out (Betts 2007). Current bat detection techniques are based on bat detectors that do not provide the surveyor with a visual description of bat activity. The use of night vision equipment can help supplement understanding of bat activity.

Surveys of species at risk from developments are essential to the preservation of the natural environment, aiding sustainable development.

1.1 *Current visual-based methods*

Manual-based surveys are commonly used during nocturnal surveys of a site. This usually involves an experienced ornithologist sampling for bird activity at different locations on the site with the aid of night vision technology, such as a light intensifier or thermal imager (e.g. Desholm *et al.* 2004). This is not always practical, if a particular location requires continuous monitoring or the potential site is hazardous or difficult to survey, such as an offshore wind farm.

Remote systems provide a realistic alternative to manual surveys by storing data for later analysis. Remote systems can reduce the disturbance of the survey on fauna, provide a back up of data for review and reduces the number of personnel required on site (Sykes *et al.* 1995). Post-survey analysis can be a lengthy, drawn out process. It requires personnel to watch through potentially large periods of inactivity until a target is spotted.

To improve the efficiency of remote systems, the use of motion or trigger detection could be used to remove the majority of periods with no target activity. This approach is becoming popular with remote monitoring, with two systems WT-Bird and Thermal Animal Detection System (TADS), developed with wind farm monitoring in mind, operating on this principle (Desholm 2003, Wiggelinkhuizen *et al.* 2006).

Basic motion and trigger detection mechanisms are liable to start recording when the target of interest is not present. For example, fast moving clouds, aeroplanes and trees shaking in the wind can cause motion, as well as birds and bats flying past. We propose approaches below to improve the detection of birds and bats, ignoring other objects that may cause motion detection.

1.2 *Detecting wing beat characteristics*

Birds and bats fly by flapping their wings, making them distinguishable from other airborne objects. By detecting this exclusive characteristic, other objects that cause false motion detection can be ignored. Benefits include speedier analysis of video data or storage space savings, thereby increasing the practicality of remote surveys, and nocturnal ecological surveys in general.

Wing beat frequencies of fauna are of interest from a number of research viewpoints. Such examples include wing beat frequencies used as a method for calculating energy expenditure (e.g. Hambly *et al.* 2004, Engel *et al.* 2006, Schmidt-Wellenburg *et al.* 2007, etc), bird identification in radar (e.g. Houghton and Blackwell 1972, Zhang *et al.* 2005,), and biomechanics (e.g. Norberg 2002).

The flapping motion exhibited by birds and bats can be described as either periodic; flapping motion repeats over time (i.e. temporally) with a fixed time period between flaps, or cyclic; flapping motion repeats temporally, but the duration between flaps varies. This non-uniformity regarding target flight can occur for many reasons. The target fauna may be soaring (wings outstretched), taking off in flight, avoiding an obstacle or merely settling into flight (Tobalske 2007). Flapping patterns can also be unique to bird groups or species (Cornell Lab of Ornithology 2007).

Another advantage of being able to detect wing beat frequencies is that a single camera can be used. Stereo cameras can provide depth information, but can be affected by a number of limitations related to monitoring distant bird targets. These include errors involved in target correspondence from both images, either through target miss-matching, quantisation and target distortion (Mohan *et al.* 1989, Rodriguez and Aggarwal 1990), and the very small disparity associated with distant targets (Shah 1997, Munoz-Salinas *et al.* 2008). As bird targets can be a few pixels in size, the further away the bird target is, the greater the error in distance calculated from stereo cameras is likely to be. Wing beat patterns are constant irrespective of relative speed or distance, and may be a more robust method for identifying bird targets that are at distance away from the camera.

There are a number of periodicity and cyclic motion detection methods available. The main types, as classified by Cutler and Davis (2000) are:

- point correspondence analysis;
- pixel periodicity analysis;
- periodic motion feature analysis;
- object similarity periodicity analysis;
- moving object rigidity analysis.

An overview of the techniques found in these categories above can be found in Lazarevic *et al.* (2007). The main review focus of the paper is on object similarity periodicity analysis based on similarity matrices and Seitz and Dyers' (1997) contribution to point correspondence analysis.

Seitz and Dyer (1997) define cyclic motion by removing the temporal constraint of periodic motion, and consider motion cyclic if it repeats, regardless of the time taken to repeat the motion. This is defined as:

$$C[\Phi(t)] = C(t) \quad (1)$$

where C is the cyclic motion, t are all times in a given domain between motion repeats, and Φ is the warping function. Seitz and Dyer use the warping function to adjust cyclic motion into periodic motion for analysis. The warping function is a variable value that adjusts the time between motion repeats until they are uniform.

Cutler and Davis (2000) check objects for periodicity by firstly aligning the objects by their tracking results. The aligned objects are then differenced against each other. The absolute values found are added to a similarity matrix. The closer the value is to zero, the more likely the frames are similar to each other. Periodic motion is detected by checking one-dimensional (1D) power spectral density using

$$P(f) = \mu_P + K\sigma_P \quad (2)$$

where μ_P is the mean power, σ_P is the power standard deviation, K is a threshold value and $P(f)$ is the peak power. Examples of applying a Cutler and Davis style approach to detecting periodic motion can be seen in the work by Lazarevic *et al.* (2007).

Plotnik and Rock (2002) also use a similarity matrix, but values in the matrix are calculated using a normalised sum of squared differences between each frame. As with Cutler and Davis, periodic motion is detected using Equation (2), and a target is identified if the autocorrelation of the similarity matrix matches a pre-defined lattice.

Branzan-Albu *et al.* (2005) is also based on Cutler and Davis (2000), but values for the similarity matrix are calculated by correlating objects with each other, and the peak correlation value used in the matrix. A global threshold is applied to the matrix, followed by a number of standard image processing morphological operators. These processes reduce the similarity matrix to a pattern based around the identity diagonal.

A key advantage of object similarity periodicity analysis based on similarity matrices, such as the methods outlined above, is that low-resolution images that may be blurry can be used (Cutler and Davis 2000). This reduces the importance of observable features such as wing size or bird shape, as the overall change of the target is compared over time, and not specific areas.

The similarity matrix based methods outlined above tend to identify a change from one type of periodic motion to another, for example, from walking to running. This approach fails to detect cyclic motion occurring within the motion. Another potential issue arises based on the number of object frames available when flying fauna cross the camera viewshed. Many flying fauna targets cross the camera viewshed within a second (pers. obs.). Considering typical video frame rates of 25 frames per second (Phase Alternating Line), the potential number of target images available is low. There may not be enough frames for lattice matching techniques used by Cutler and Davis (2000) and Plotnik and Rock (2002), and the morphological operations used by Branzan-Albu *et al.* (2006) may cause most of the similarity matrix information to be lost.

2. Proposed method

The methods outlined above all use similarity matrices as part of the process for finding periodicity based on spectral frequency analysis. It is proposed that the similarity matrix can be used to identify cyclic motion based on the pattern formed by the matrix.

A similarity matrix is a way of determining relationships between signals, or a single signal (self-similarity). This method can provide a visual or numeric representation of correspondence within the signal, displaying a relationship between signals or within a signal. Applications for similarity matrices include genetic (e.g. Borowski *et al.* 2000) and music analysis (e.g. Muller and Kurth 2006). An illustration of how a similarity matrix can be used is presented as follows.

An oscillating numerical series of {1, 3, 5, 3, 1, 3, 5, 3, 1} is plotted against itself in a similarity matrix (Figure 1(a)). The result of the difference for each term over time is placed in each element (Figure 1(b)). The lower the value, the more similar the terms of the series are, and the larger the value, the more different they are. A pattern within the matrix suggests a periodic or cyclic relationship is present within the series. Finally, providing a shading reference to the elements, using black to represent zero and white to represent the maximum difference (four in this instance), a visualisation of the pattern is presented (Figure 1(c)). Measuring the number of elements between crossover peaks of similarity (black elements) identifies how often the series repeats (every four elements in this instance).

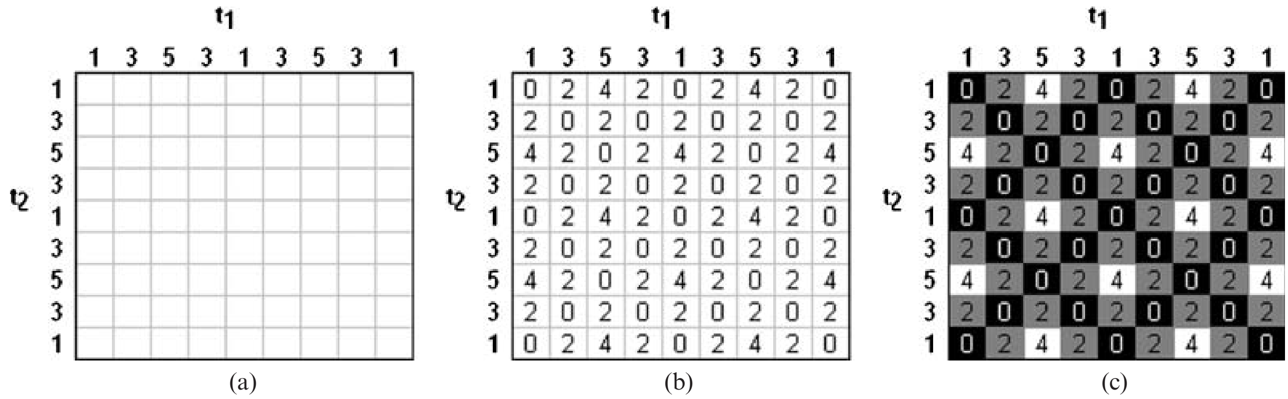

Figure 1. Similarity matrix illustration using a number series. (a) The series plotted against itself. (b) Series terms differenced over time. (c) Colour-shading of elements to provide a visual interpretation.

A number of scenarios have been produced to represent different types of periodic and cyclic motion. In each scenario, the vertical values of the black pixels represent 1D data of an event, while the horizontal of the scenario represents the time at which that event occurred. Looking at the scenario overall shows what action is happening. A similarity matrix has been generated for each scenario using the following:

$$S_{t1,t2} = k \sum \left| O_{t1_{(x,y)}} - O_{t2_{(x,y)}} \right| \tag{3}$$

where t1 and t2 represent the temporal periods between the 1D data value O and S are the values plotted in a similarity matrix. The threshold value k is a constant; 0.01 was used in this instance. The more similar two frames are, the darker the representative pixel will be on the matrix. Brighter pixels correspond to less similarity between frames. The diagonal running from the top left corner to the bottom right corner is always zero, i.e. black as a frame will always be identical with itself.

Looking at simulated data put into a similarity matrix there are intuitive, observable differences between cyclic motion and randomly generated noise, as can be seen in Figure 2. Where cyclic motion is present, the pattern in the similarity matrix generated suggests something interesting is happening. Where there is no cyclic motion, there is either no obvious intuitive activity as in Figure 2(e) or no evidence of repeating motion, as in Figure 2(f).

The next step forward is to interpret an observer's intuition of activity from a similarity matrix to a method for identifying it. One of the key assumptions made for identifying cyclic motion is that high amplitudes of cycles are most likely to be found at low frequencies. Noise in the similarity matrix due to frame capture, spurious pixels and poor segmentation is most likely to occur at higher frequencies. However, it is important to try and avoid dismissing cyclic motion with poor temporal matches between repeating motion, which may occur using Equation (2). The following is proposed. The peak power amplitude frequency was found, and a low pass top hat filter was applied, effectively smoothing the image, removing periodicity that is likely to have been generated by noise. An Otsu threshold (Otsu 1979) is applied to the image. A 3×3 Sobel edge detector is then applied to distinguish between a discernable pattern in the similarity matrix from cyclic motion (mostly background pixels, few edge pixels) and noise or a nonsense similarity matrix (high proportion of edge pixels, or a very low number of edge pixels). Figure 3 illustrates the above using a number of 1d data inputs. Figure 3(a) and (b) use cyclic data, whilst figure (c) and (d) use non-cyclic 1d data.

2.1 *Applying the method to real data*

Clips of flying fauna were used to generate similarity matrices. Fauna included: a bat, Harris Hawk *Parabuteo unicinctus*, Golden Plover *Pluvialis apricaria* (captured using a cooled thermal imager connected to a USB digital frame grabber) and Rook *Corvus frugilegus* (captured using a digital video camera). All frames from all clips were converted to 256 greyscale level images prior to any processing.

There are a number of background subtraction techniques available. The method applied in this paper is based on an adaptive running average (Heikkila and Silven 1999). More advanced methods are available, but this approach provided good results, as rapid illumination changes, reflectance and shadow do not affect thermal imagers.

For the bat and Harris Hawk clips, the targets were segmented from the background by differencing

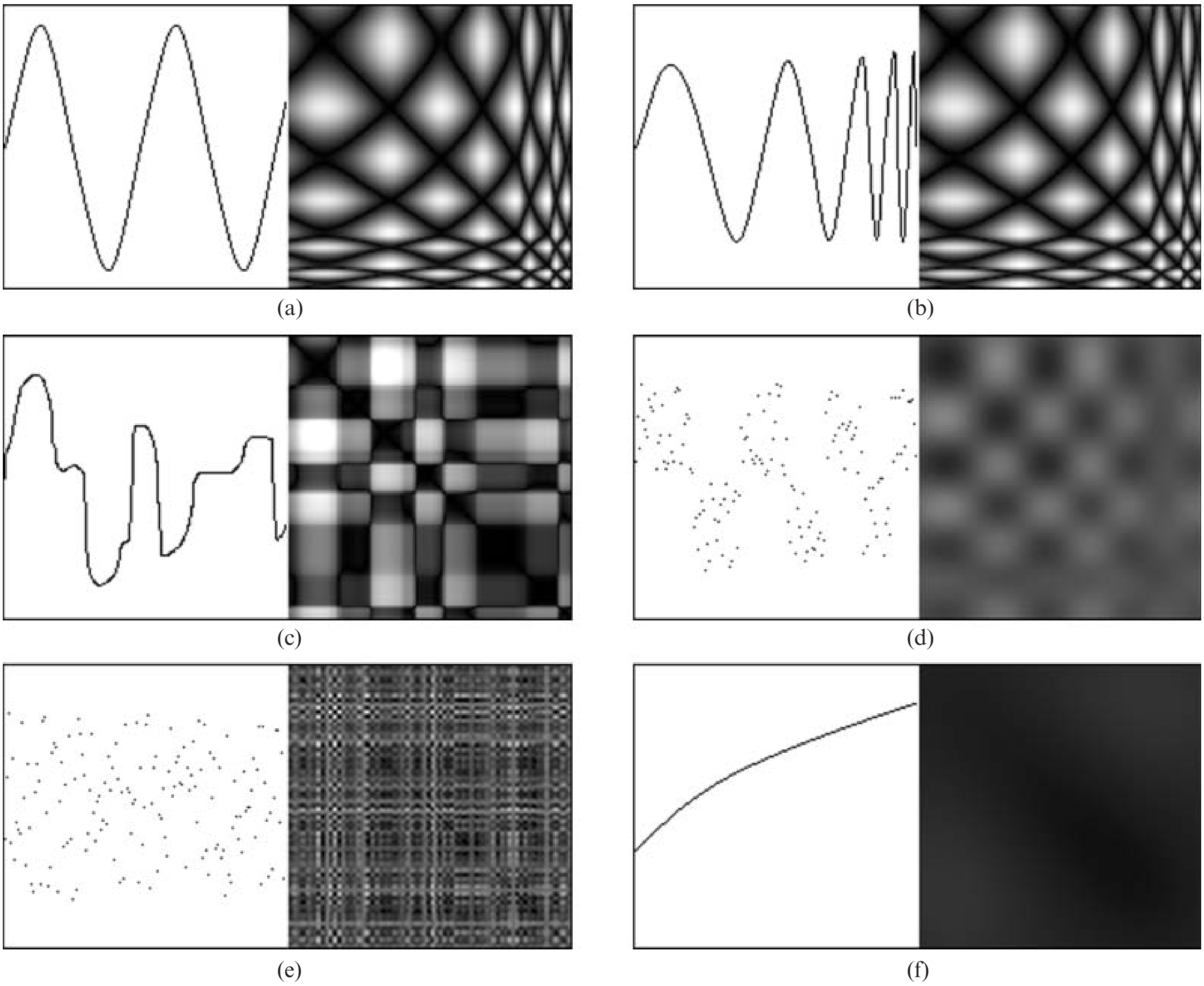

Figure 2. Examples of cyclic motion and their similarity matrices. (a) A periodic sinusoidal wave. (b) Sinusoidal wave that increases frequency with time. (c) Representation of erratic flapping motion that has similar repetitive motion. (d) Random points that reasonably fit a square wave that increases frequency with time. (e) Randomly generated points. (f) Point values that gradually increase over time. All matrices are made up of 150 points.

the current frame from an updated background model. The background model was updated using

$$B_{t+1} = (1-\alpha)B_t + \alpha I_t \tag{4}$$

where B_t is the current background, I_t is the current image frame, α is the learning rate (set at 0.05) and B_{t+1} is the updated background. The initial frame used was an empty frame. The adaptive background was differenced with each frame in the sequence where;

$$|I_t - B_t| > T \tag{5}$$

where T is a fixed threshold value of 17 greyscale levels. This value is based on testing a number of values that reasonably separated the target from the background. The bat crossed the camera viewshed in 16 frames, the Harris Hawk crossed the viewshed in 19 frames.

The Golden Plover and Rook were hand-segmented frame-by-frame from the video clips. The Golden Plover crossed the camera viewshed in 19 frames while the Rook crossed the viewshed in 18 frames.

All of the fauna apart from the Rook flew in a linear manner across the viewshed. The Rook changed direction of flight and its body positioning during its flight across the viewshed.

Regardless of the segmentation method used, all targets were aligned by their centre of gravity. As with the simulated data, each target's similarity matrix was created using Equation (3).

Once the similarity matrices had been generated, a low pass filter, as described previously was applied to the matrices, along with the Otsu threshold.

3. Results

The visual results of each stage of the cyclic motion detection method applied to the birds and bat data are shown in Figure 4. The similarity matrices appear to visually show flapping data. Figure 5 shows the series of clipped frames as the bat target crosses the camera viewshed. The bat extends its wings near the start of the frame sequence and near the end. The similarity matrix for the bat (Figure 4(a)) shows this with the largest dissimilarity coinciding with the full extension of the wings.

The Golden Plover similarity matrix shows a more rapid wing beat compared to the bat. This can

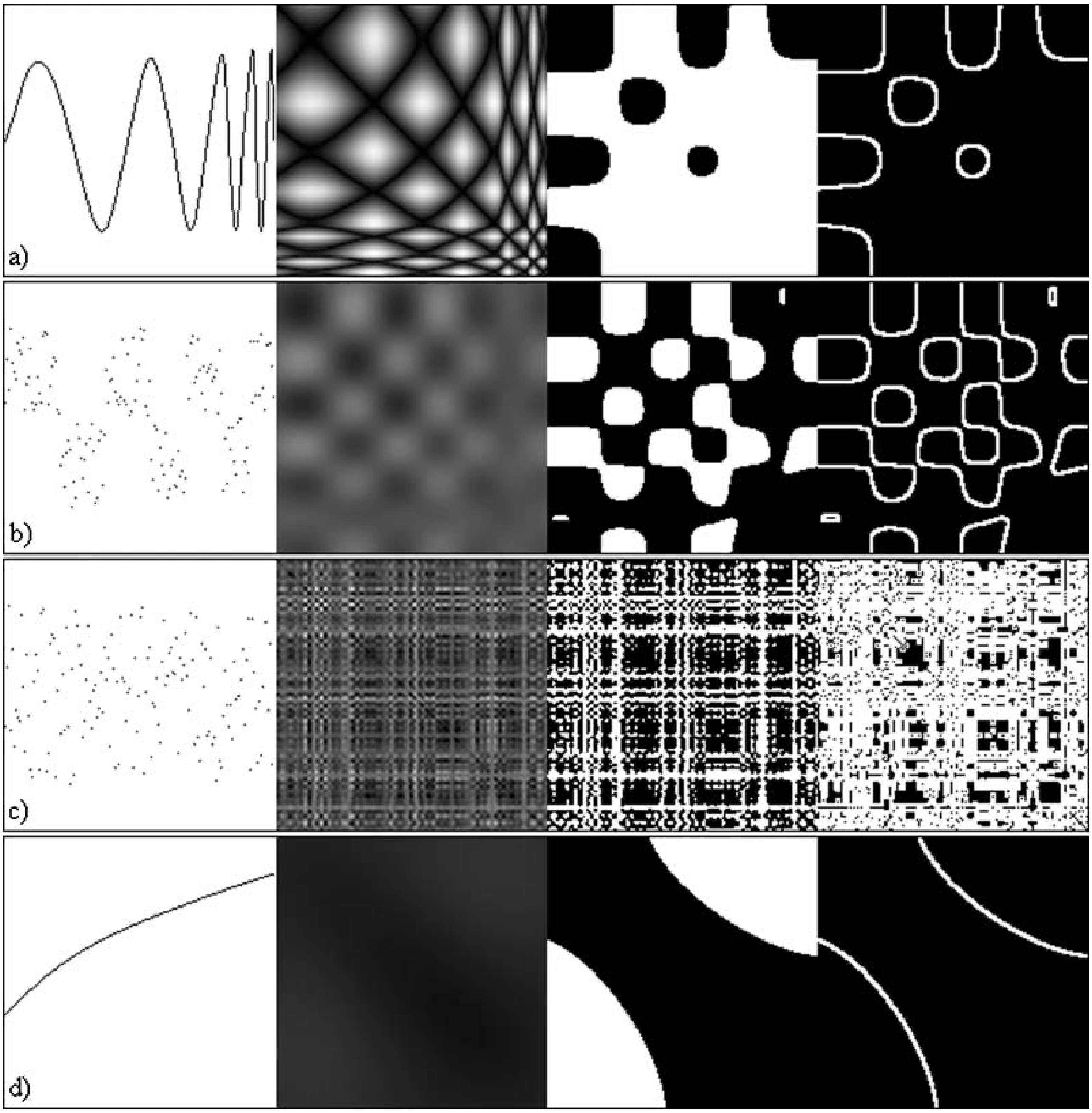

Figure 3. Cyclic motion detection stages. From left to right, original simulated data, similarity matrix, similarity matrix after low pass filter and Otsu threshold applied, similarity matrix after edge detection applied. (a) Sinusoidal wave that increases frequency with time. (b) Random points that fit a square wave that increases frequency with time. (c) Randomly generated points. (d) Point values that generally increase over time. All matrices are made up to 150 points.

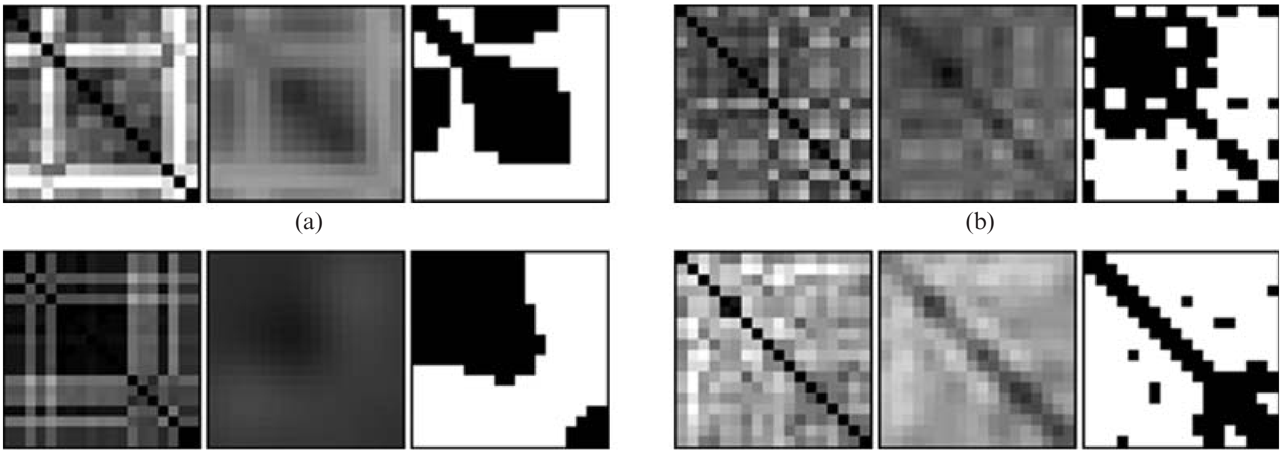

Figure 4. Cyclic motion detection for flying fauna. (a) Bat, (b) Golden Plover, (c) Harris Hawk, (d) Rook. Left image – similarity matrix; middle image – lowpass filtered image; right image – Otsu threshold image. All images have been enlarged by 400%.

be seen with the grid-like structure within the matrix. The Harris Hawk similarity matrix shows a flap, followed by a soaring period, followed by a flap. The poor definition in the first flap in the matrix is due to poor segmentation in a couple of the frames. The Rook similarity matrix has some texturing, but it is difficult to ascertain cyclic or periodic motion within the matrix. However, there are still some 'clumps' visible in the threshold image.

4. Discussion and conclusion

Effective bird and bat surveys are essential to improving the sustainability of new developments. The use of motion detection can be used to develop and widen the application of remote surveys for monitoring bird and bat activity. Further enhancements can be made to fauna detection by capitalising on distinct flapping features, without necessarily requiring distinguishable features such as wing and body shape, hence operating on low-resolution images.

Birds do not always fly with periodicity. Flapping variation can depend on types of flight, time length during wing oscillation and time length between wing oscillations. If target motion changes are used as a tracking method, it is important to consider cyclic oscillations in addition to periodicity.

It has been shown that cyclic motion, as well as periodic motion, can be represented in similarity matrices. A pattern can be manually observed from the matrix when an object exhibits cyclic or periodic motion. This is in contrast to when only noise is present, or the object does not oscillate while moving.

This approach has been applied to video clips of flying fauna. As with the simulated data, the similarity matrices showed distinctive patterns for each fauna example. This is useful where a limited number of frames are available. A limitation is likely to arise when there are too few frames to generate a similarity matrix. This situation is most likely to occur when a bird target is flying past the camera at a close distance. More distant targets are expected to generate a number of frames that will generate a satisfactory similarity matrix.

Bird species have varying flap patterns as well as different wing beat frequencies. It is possible to an extent to determine these flap patterns for a species from the similarity matrix. This may potentially be useful for identifying fauna species groups, further improving the efficiency of automated remote survey systems. Appropriate image processing methods such as smoothing and thresholding applied to similarity matrices may be able to provide a suitable template for target identification based on the matrix's pattern. This may displace some of the errors associated with stereo vision, and reduces the cost associated with an additional thermal, making small-scale nocturnal fauna surveys more practical.

Automating the segmentation task would make the proposed method more practical in real-time applications. A suggested approach could include the

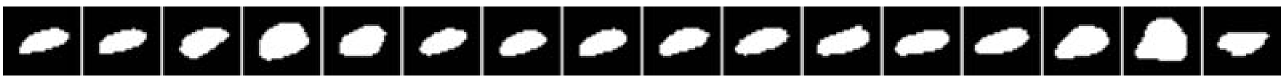

Figure 5. Segmented frames of bat target crossing the camera viewshed.

use of a Kalman filter to distinguish genuine moving targets from noise, applied to blobs found after the running average method as described previously has been applied. Target centre of gravity can be used as the tracking point. As targets can vary in size, all blobs may have to be treated as potential targets until the Kalman filter 'rejects' it by being unable to locate the target at the next 'predicted' location. Specific target segmentation can be achieved through background subtraction. How well this method segments a target compared to hand segmentation, and the robustness of the cyclic motion detection based on sub-optimal segmentation would need to be explored.

5. Future work

Edge detection has yet not been applied to the real bird images, but this will be undertaken as future work.

Research will be undertaken into how processed similarity matrices can be used for identifying species groups. In addition to species group identification, determining the minimum number of frames required for generating matrices will be investigated.

Acknowledgements

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Approaches to measure wing beat frequencies with computer vision

LJUBICA LAZAREVIC[12], DARREN SOUTHEE[1], DAVID HARRISON[1], JOHN OSMOND[1], DARREN FROST[2], MAX WADE[2]
[1]School of Engineering and Design, Brunel University, Uxbridge, UK
[2]RPS, St Ives, UK

ABSTRACT

Windfarms are one of the most popular resources for generating renewable energy, and seen as one of the tools that can aid the UKs reduction in carbon emissions. However recently wind farms have received much criticism regarding the potential negative impact they may have on ecology, in particular, birds. Wind farm proposals, as with other developments, must be accompanied with an Environmental Impact Assessment (EIA).

A lot of concern regarding bird collisions with wind farms comes from periods of poor visibility at night. To understand the impact these conditions can have on birds, nocturnal surveys are necessary. Technologies that aid nocturnal bird surveys, such as night vision and video gathering equipment can be expensive due to the analysis time required to review the video.

Monitoring systems that reduce analysis time and provide information on bird activity at night are available, but they can be limited in where they can operate, and detection accuracy rates can be low. Identifying features of birds, such as wing beats, may allow novel computer vision methods to recognise and differentiate between species, thereby increasing the range where monitoring systems can operate and their accuracy. This paper reviews several periodicity detection methods. Two techniques reviewed were adapted and implemented and the produced results were assessed.

1 BACKGROUND

One of the goals of the United Nations Environmental Programme (UNEP) is to encourage member states to adopt the principles of sustainability. Two topics of importance to UNEP as part of their aims of sustainability are through the implementation and use of renewable energy technology such as wind farms, and the protection of protected species and biodiversity (UNEP 2006).

In a bid to reduce carbon emissions in the UK, legislation has been put in place to reduce carbon emissions from conventional energy generating technologies. The Renewables Obligation (R0) requires all electricity suppliers to source or generate at least 10% of supplied electricity from renewable sources by 2010 (BWEA 2005). Wind power is one of the most developed and readily available renewable technology (BWEA 2005) making it one of the most feasible ways for energy suppliers to meet the criteria specified by the RO.

Birds have long been regarded as potential indicators for the health of the wider environment (Louette and Bijnens 1995). They are considered to be good general indicators of the broad state of wildlife, due to living in many different types of habitat (Gregory et al. 2004). Their high occurrence, abundance and reproductive success are all based on their surrounding habitat (Carignan and Villard 2002).

There has been some concern that wind farms have negative impacts on birds. The Royal Society for the Protection of Birds (RSPB 2005) has said ‘poorly sited wind farms can cause severe problems for birds, through disturbance, habitat loss/damage or collision with turbines’. Offshore wind turbines may become one of the largest technical interventions in marine habitats in Europe (Exo et al. 2003). A study into flight patterns of long-lived wildfowl across a wind farm was conducted with radar. The study revealed that during the night, migrating flocks were more likely to enter the wind farm than during the day (Desholm and Kahlert 2005). There are three main concerns relating to windfarms and birds. They are collision, barrier effect and displacement (Exo et al. 2003, Bairlein 2004).

In an attempt to reduce potential environmental impacts on the environment, such as wind farm impacts on birds, schedule one developments (see the Town and Country Planning regulations 1999 for a list of schedule one developments) are subject to an Environmental Impact Assessment (EIA) being carried out prior to planning permission being granted. A carefully positioned wind farm, where positioning can be determined through careful planning, is unlikely to pose a significant threat to birds (RSPB 2005).

An EIA is a decision making tool. It is used to identify potential environmental impacts of a potential development. The EIA presents the likely effects of the development so that all stakeholders are aware of the development (DCLG 2000). An EIA promotes and encourages ‘sustainable patterns of physical development’ (DCLG 2000). As part of the EIA process, there is a preliminary consultation to determine the potential environmental impacts of the proposed development. Specialists can provide the developer with information on environmental factors at risk (DCLG 2000).

Potential impacts of a development on birds are typically judged from information collected on bird activity and abundance in the proposed development area. Diurnal surveys are typically used to determine distributions of birds, such as shorebirds over areas that are determined to require protection (Gillings et al. 2005), but this assumption can be misleading. Flock behaviour can differ between day and night with different land and habitat uses (Gillings et al. 2005, Mouritsen 1994, Sitters et al. 2001). Predicting future nocturnal activity from diurnal surveys alone can produce inaccurate scenarios. Nocturnal surveys must be used to supplement diurnal surveys in order to achieve a balanced representation of bird activity. Without nocturnal bird surveys, stakeholders may register objections against a wind farm development if nocturnally active birds are at risk, and it may not be possible to put all required information into an EIA.

Nocturnal bird surveys provide much information about bird activity at a development area, and this information can be used in the preliminary stages of construction to prevent negative impacts on the ecology in the area. Limitations in our vision make nocturnal surveys without specialist equipment difficult.

1.1 Current methods

Due to our poor vision at night, specialist night vision equipment such as thermal imagers and light intensifiers are used to assist nocturnal surveys. Night vision equipment is typically attached to a video recording device for the duration of the survey. Once the video is collected, skilled ornithologist operators view the video to detect and identify bird activity. This method is very time intensive and can be costly due to the man-hours involved. The methodology presents even greater limitations if a long-term study is required, as for each hour of data recorded, at least an hour is required by the operator to view it in addition to breaks to avoid fatigue. The high costs and technical expertise that are associated with these methods have caused relatively limited application of nocturnal surveys for monitoring bird activity.

To make these methods more accessible and practical, these time-based limitations have encouraged research into reducing the amount of time an operator requires to spend looking at video. The focus has been on removing periods of inactivity from the video, to reduce the data for assessment by the operator.

There are currently two systems, used in wind farm monitoring, that have been heavily tested that try to remove periods of bird inactivity. These are WT-Bird (no acronym), and TADS (Thermal Animal Detection System). WT-Bird is based on having microphones and accelerometers installed onto a wind turbine and it's blades and is used to detect bird collisions. When a bird collides with the turbine, the system detects the impact noise, and then stores buffered video to permanent storage. However, there are many background noises, such as turbine operation, and the system currently has a success rate of 40% under controlled conditions (Wiggelinkhuizen et al. 2006). The system also fails to record near misses and collisions due to blade turbulence, which could potentially be important information regarding bird avoidance. TADS is based on detecting birds moving into the cameras field of view through temperature-based thresholding. However, the system depends on cloud-less skies and is prone to false triggers (Desholm 2003).

As seen above, there are limitations in the currently available systems that need addressing. To improve the efficiency of remote bird monitoring, research into monitoring bird activity is taking place.

1.2 Improving the method

Birds can be differentiated from other objects such as clouds as they typically flap their wings with periodicity. By identifying objects within the video that display periodicity, it can be reasonably assumed that those objects are birds.

There are two ways a bird's wing beats in a video can be identified. The first identifying feature is when a bird target is relatively near to the camera. Its wing beats can be clearly observed as wings generally oscillate about the horizontal point of the bird's body. The second identifying feature is when a bird target is far from the thermal imaging camera, and it is not possible to see the birds' wings oscillate. There is an observable 'blinking' of intensities as the bird moves across the field of view. This is due to a relatively warm body being periodically obscured by a relatively cold wing. Any method that is used for identifying periodicity needs to be able to robustly handle both types of wing beats.

1.3 Wing beat frequency

There have been several techniques and methods of implementation that have been suggested by various authors based on detecting periodic, non-rigid motion. These techniques are categorised as follows, according to Cutler and Davis (2000):

- Point correspondence analysis
- Pixel periodicity analysis
- Periodic motion feature analysis
- Object similarity periodicity analysis
- Moving object rigidity analysis

Most of the techniques that were reviewed were composed of two stages. The first stage involves some form of segmentation to identify the object for analysis, and the second stage is the periodicity analysis/detection. As some of the techniques used for segmentation claim to be robust to clutter, a brief overview is provided.

1.3.1 Background segmentation

Cutler and Davis (2000) use a background model that is based on the temporal median of a pixel, typically over 50-200 frames. If colour images are available, then each RGB colour component is used to create the temporal median background model. A binary image is then produced by marking pixels that are greater than the sum of the median image with the product of the standard deviation with a constant (typically 10). Small components are removed, and any objects are added to an object-tracking list.

Rife and Rock (2001) use gradient magnitude thresholding for detecting jellyfish. Morphological opening and closing is then applied to the image to remove small components.

Polana and Nelson (1997) calculate the normal flow magnitude at each pixel over consecutive frames. Pixels with significant motion, which are most likely to represent a moving target are marked by thresholding them with respect to the normal flow magnitude.

1.3.2 Overview of periodicity detection techniques

1.3.2.1 Techniques based on point correspondence

Point correspondence techniques look to see how motion may repeat itself by taking a point or points of an image, and then monitor how the point displacement changes across the image (spatial change).

Tsai et al. (1994) fit a trajectory curve of how a selected point moves over a number of frames. The curvature of the curve is then calculated by fitting it to a quadratic surface-fitting algorithm. Once the curve has been extracted, autocorrelation is applied to check for any peaks that would reveal periodicity in the motion.

Seitz & Dyer (1997) use temporal correlation plots for repeating motion without the use of object tracking. There are features within the technique used by Seitz & Dyer that allows the method to monitor repeating motion, rather than motion with constant periodicity, and can monitor non-rigid objects in motion.

1.3.2.2 Pixel-level analysis for periodicity

Whereas point correspondence looks at how a specific point varies spatially on a set of images, pixel-level analysis looks at how specific pixels vary temporally over a set of images, i.e. how does a pixel in a certain position vary over time.

Polana & Nelson (1997) align objects in a sequence by their centre of gravity and then extract reference curves. Spectral energy is estimated along the curves, and periodicity is measured based on spectral energy differences from the curves.

Liu & Picard (1998) track foreground objects, which are then aligned by their centroid, and formed into an image block. An example of an image block can be seen in figure 2. An XT slice at the ankle level of the tracked object is taken, and 1D Fourier analysis is applied to the centre column of the slice. The power spectrum and harmonic energy reveal periodic motion.

1.3.2.3 Periodic motion feature analysis

Methods based on periodic motion feature analysis work on identifying features in the image, and then look for periodicity generated by the selected features over time.

Fujiyoshi & Lipton (1998) build a feature model by segmenting the object of interest, and producing a star skeleton from the objects’ boundary. Fourier analysis is then carried out on the angle differences produced by parts of the skeleton, and signal correction and autocorrelation is carried out to determine periodicity in the analysed motion. An example of this is illustrated in figure 1.

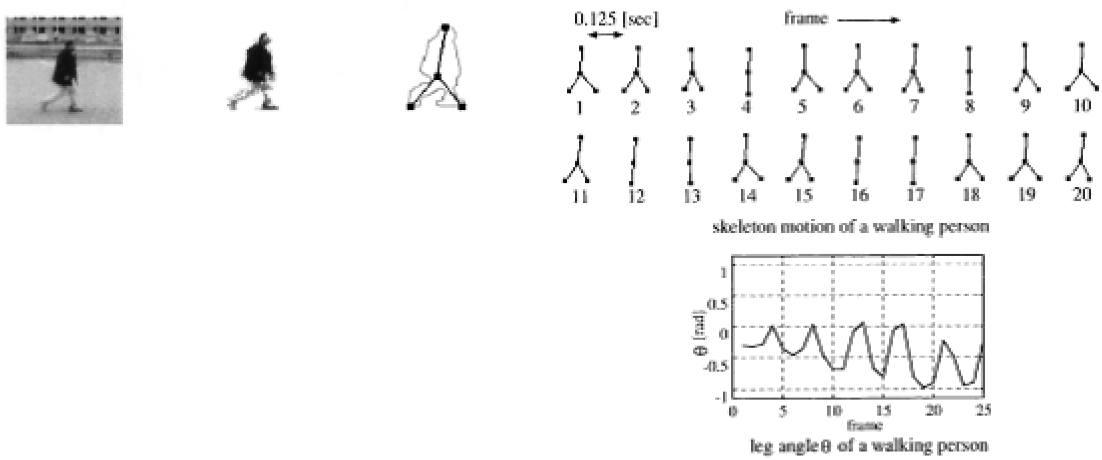


Fig. 1 a star skeleton is made from the objects boundary. The skeleton is monitored over a number of frames and leg angle is plotted (Fujiyoshi & Lipton 1998)

Niyogi & Adelson (1994) use a similar method to Liu and Picard (1998) by focusing on the XT slice at the ankle level of the observed target (figure 2) but unaligned. Templates are then used to find the distinctive braided pattern in the XT slice. An XT slice consists of the temporal changes of x pixels over time.

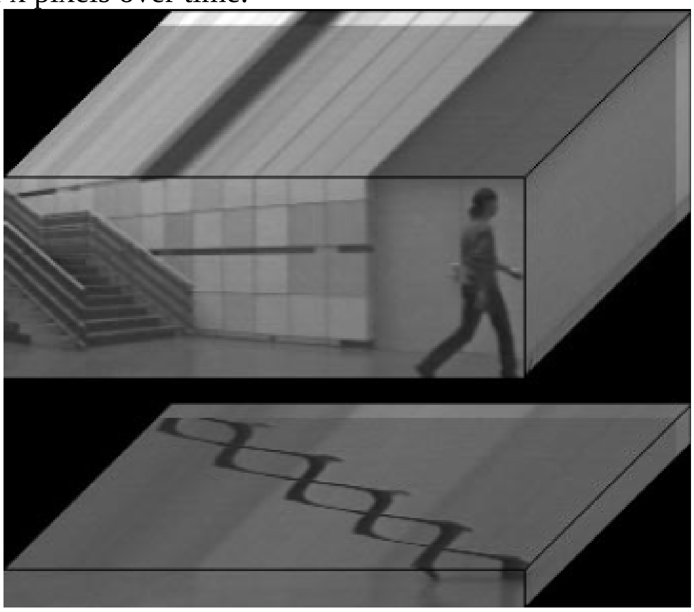


Fig. 2 an example of an image block which consists of images stacked over time (Niyogi & Adelson 1994)

1.3.2.4 object similarity periodicity analysis

Rather than looking at temporal changes at the pixel level, object similarity periodicity analysis looks at how the whole object changes temporally. This is achieved through comparing the object with itself over time.

The Cutler & Davis (2000) technique works by aligning an object by its centre of gravity, and then differencing the object with itself temporally. The results are used to produce a similarity matrix. Repetitive, periodic motion is then detected by applying a threshold to a 1D power spectral density. The dark parts of the similarity matrix indicate periodicity within the stack of images.

Plotnik & Rock (2002) use a similar method to that put forward by Cutler & Davis and a similarity matrix is produced. The frequency of the motion is found through applying autocorrelation to the similarity matrix, and then fitting a lattice over the local peaks.

1.2.3.5 Determining moving objects through analysis rigidity

These methods look at trying to determine whether an object is rigid or non-rigid. They do not strictly look for periodic motion, but do offer a useful function of differentiating between objects that are rigid, such as vehicles, and non-rigid, such as humans, animals, and other moving objects.

Selinger & Wixson (1998) use a similar method as used in object similarity, but rather than calculate a temporal difference, they calculate a spatial distance between the objects in two positions. The distance is plotted over time, and if it is sinusoidal, then the motion is repetitive and periodic.

2 ADAPTING AND APPLYING PERIODICITY DETECTION TECHNIQUES

To see how some of the above techniques could be applied to detecting bird flapping periodicity, two techniques, one based on representing motion through transforms, and the other based on area difference were adapted and applied to types of data that represent possible scenarios from a nocturnal bird survey.

2.1 Representing motion through transforms

The aim of implementing motion through transform is to see whether there are any obvious repeating patterns that could be used to identify repetitive motion within a series of frames.

2.1.1 Method

The data to use with motion through transforms was generated as follows. A volunteer was recorded walking across a relatively stable, cluttered scene and a constant place. To represent the motion of a bird, the volunteer flapped his arms as he walked across at a constant place. To distinguish the volunteer’s arms from his clothing, white markers were placed on his arms (figure 3). The volunteer maintained a parallel path with the camera. This removes the need to apply alignment correction for movement across the Y-axis.

Fig. 3 volunteer flapping

A total of 40 frames were generated. The frames were stacked together sequentially to create an image block (standard x-y axes with the third axes, t representing temporal changes). The height (y) values that crossed through the ankles and through the white marker on the arm when it was lowered were selected, and two XT slices were extracted.

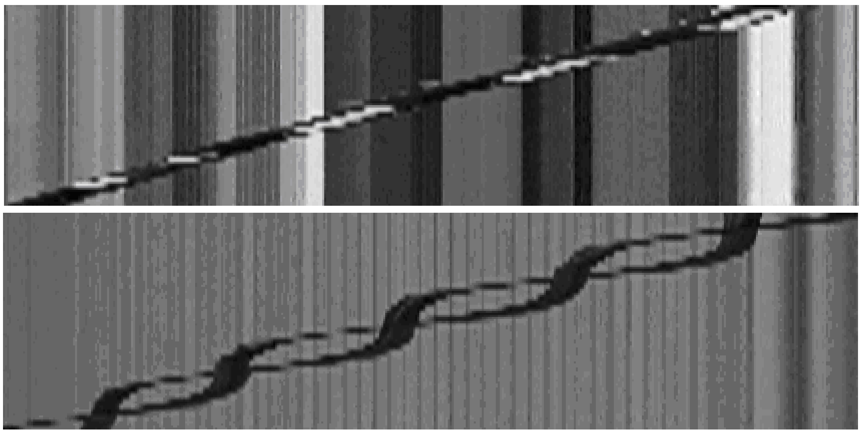
2.1.2 Results

The XT slices that were extracted are shown in figure 4. Figure 4 (a) shows the slice taken across the lowered arm with the marker, and figure 4 (b) shows the slice taken at the ankle level. The ankle slices shows the recognisable braiding pattern usually obtained from applying the transform. The crossing points of the braid represent when the volunteers ankles cross during the walking, hence the pixel distance of the height (the number of frames) between where the braiding crosses provides us with half of the period (the full period occurs when the legs are back at their original position). Calculating the period (T) of the walking is as follows:

$$\mathbf{T = 2dT/Fr} \qquad \mathbf{(1)}$$

where Fr = frames per second, and dT is the number of vertical pixels between where the ankles cross.

The arm-level slice shows a white dashed line, with the white from the marker worn by the volunteer. The dark black line between the dashes is from the volunteer's dark clothing. The same principle for determining periodicity from the braid resulting for the ankle can be applied here, by measuring the distance between white dash midpoints to the midpoints of the following black dash, and dividing by the frames per second.



(a)

(b)

Fig. 4 XT slices. (a) arm level slice (b) ankle level slice. Both slices have been stretched for illustration

2.2 Area-based periodicity detection

To see how area-based differencing and comparison can be applied in periodicity detection.

2.2.1 Method

Two sets of data were used to investigate area-based differencing. The first set of data is used to model the situation when a bird is 'blinking'. This is achieved through changing the intensity of a dot over time. Noise is added to the blob, and the rate of change between light and dark is not completely linear (figure 5(a)). The blob returns to light intensity every 22 frames. A total of 50 frames are used. The second set of data is of a rotating turbine that was recorded using a thermal imager. The frames have a threshold applied to remove most of the background prior to use (figure 5(b)). The turbine assumes the same position every 33 frames. A total of 150 frames are used.

(a) (b)

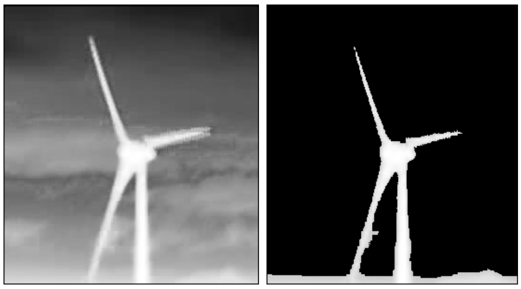


Fig. 5 the test data. (a) The dots with changing intensity. (b) The rotating turbine and the turbine with a threshold applied

Differencing is applied to each set of data. Each frame in time is differenced as follows:

$$\mathbf{S_{t1,t2} = k\Sigma\ |O_{t1(x,y)} - O_{t2(x,y)}|} \qquad \mathbf{(2)}$$

where S is the similarity matrix, t1 and t2 represent the period between the frames, k is a threshold constant, 0.01 used in this example, and O is the frame. The S values are plotted in a similarity matrix.

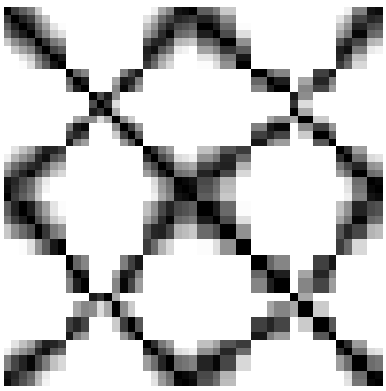
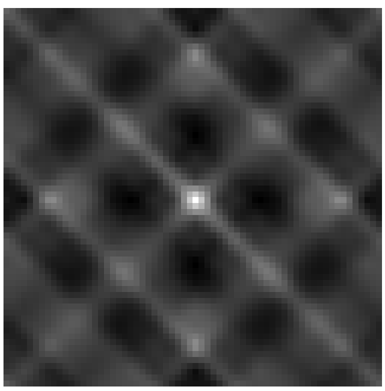
2.2.2 Results

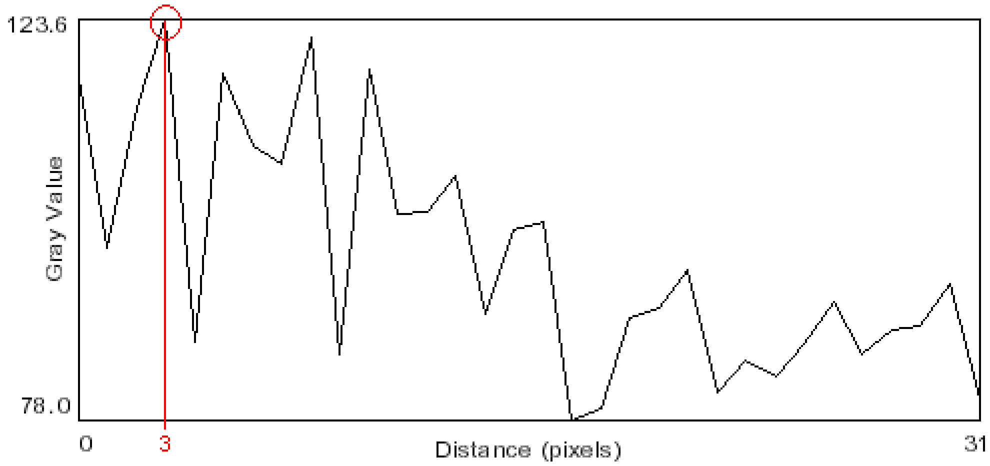
The similarity matrices for the intensity-changing dot and for the turbine are shown in figures 6(a) and 7(a). Both similarity matrices show pattern repetition, which indicates the object has reoccurring activity/phases. Periodicity in the form of clearly visible lattices is observed from the dot example. However, identifying the reoccurring periodicity pattern from the turbine similarity matrix is less obvious. To highlight periodic motion within the similarity matrix, autocorrelation is applied. The autocorrelation image for both similarity matrices can be viewed in figures 6(b) and 7(b). Measuring the distance between pixels shows the duration of the motion in pixels. Fourier analysis can be applied to a similarity matrix to identify the most common frequency. This is illustrated in figures 6(c) and 7(c). The peak frequency for the peak amplitude shows the most likely frequency for the object's motion. The power spectrums shown here were obtained by applying a fast Fourier transform (FFT) to the similarity matrices. Obtaining the period (T) of the objects motion from the power spectrum can be obtained using:

$$\mathbf{T = X_f / F} \qquad \mathbf{(3)}$$

where X_f is the length of the FFT image in pixels, and F is the frequency of the maximum amplitude from the power spectrum.

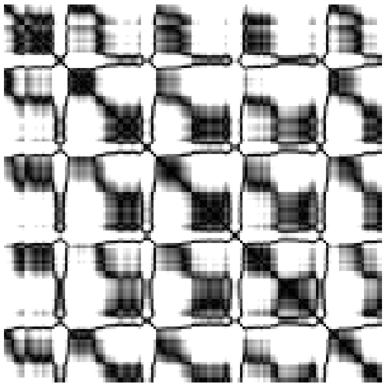
Using (3) to calculate the period from the power spectrum, for the dot, $T_d = 64/3 = 21.3$, compared to the known periodicity of 22, and for the turbine, $T_t = 256/8 = 32$, compared to the known periodicity of 33. As a FFT image consists of positive and negative frequencies, we are only interested in the positive frequencies for obtaining the power spectrum, so the power spectrum is determined from the positive quarter of the FFT image.

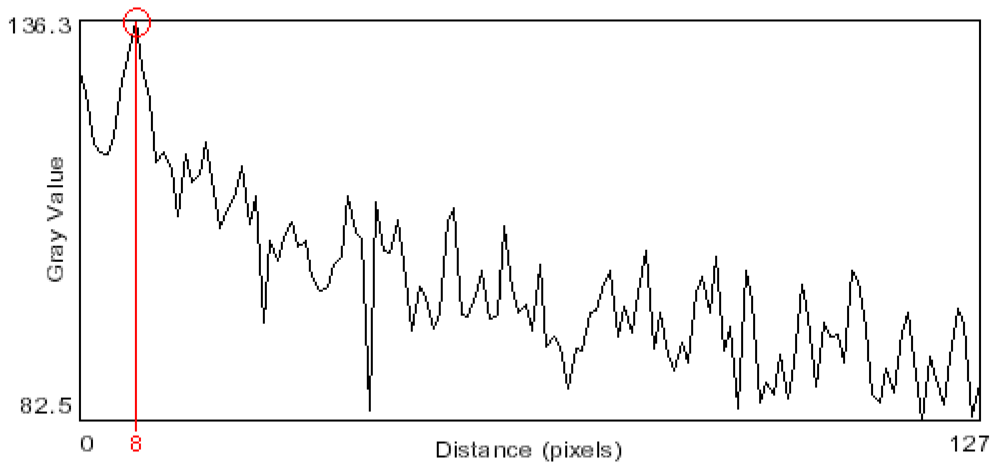
(a)  (b) 



(c)

Fig. 6 (a) The similarity matrix for the dot over 50 frames (b) the autocorrelation image of the similarity matrix (c) The positive quarter of the FFT power spectrum of the similarity matrix. The peak is highlighted, and the frequency (F) is found to be 3

(a)  (b) 



(c)

Fig. 7 (a) The similarity matrix for the turbine over 150 frames (b) the autocorrelation image of the similarity matrix (c) The positive quarter of the FFT power spectrum of the similarity matrix. The peak is highlighted, and the frequency (F) is found to be 8

3 DISCUSSION

Representing motion through a transform provided a clear and distinct braiding pattern at the ankle slice. However, the slice at the arm level did not produce as clear a pattern, producing a dashed line.

Area-based periodicity detection provided very clear periodicity from the two test examples. Applying autocorrelation to a similarity matrix further enhanced the visible periodicity in the similarity matrices, and the power spectrum of the similarity matrix provided a straightforward method for determining the period of the object's motion.

4 CONCLUSION

Two potential methods that can describe the periodicity of an object have been adapted, implemented and tested. The first technique, obtaining a 'motion' transform did not provide a very promising way of determining periodicity from the data that was a mock up of a flapping bird. The technique is very much dependent on there being a contrast between the object being observed and the background, in addition to having visible limbs moving periodically away from the main body of the target. The method is also reliant on the motion being similar and the object not changing direction.

Area-based periodicity detection provided very promising results. The technique is very flexible to the objects appearance, and robust to varying levels of object segmentation. Area-based periodicity was able to identify periodicity in both varying intensities and repetitive periodicity through motion. The straightforward methods available for determining periodicity from the similarity matrix produced from area-based periodicity makes the technique very favourable for applications in detection birds. Future work will be based on applying the technique to bird targets.

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CAN TEMPLATES BASED ON SIMILARITY MATRICES BE USED TO IDENTIFY GOLDEN PLOVER?

L. Lazarevic(1,2), R. Ward(1), M. Wade(1), D. Harrison(2) and D. Southee(2)

1. RPS, Compass Point Business Park, St Ives, Cambridgeshire
2. School of Engineering and Design, Brunel University, Uxbridge, Middlesex

Abstract

Bird and bat surveys are an important element in determining potential ecological impacts of certain developments. Automated nocturnal bird surveys are becoming increasingly popular. They greatly reduce the amount of time required by personnel to review survey data. Triggers or motion detection in the system will commence and cease video recording of activity. Yet fast-moving clouds and other objects can also cause detections. It is desirable to remove this unwanted data.

As birds and bats change shape as they fly, it is difficult to use spatial-based features to distinguish these fauna from false targets. The oscillatory wing movement birds and bats make distinguishes them from other airborne objects. Detecting this motion can reduce the number of false events recorded by an automated system.

Past-presented periodicity detection methods using area-based correspondence are not always successful in detecting all bird flight types. Similarity matrices based on temporal motion of a target can be used to detect cyclic motion. A new application for similarity matrices is discussed, which could be potentially used to classify fauna groups. Initial trials of the method have been carried out to test whether Golden plover can be identified from other flying fauna. Based on correlation, a kernel is created from an existing Golden plover similarity matrix, which is used to find matching patterns in other similarity matrices.

Keywords: Birds, bats, wing beat frequency, cyclic motion.

CAN TEMPLATES BASED ON SIMILARITY MATRICES BE USED TO IDENTIFY GOLDEN PLOVER?

1.0 Introduction

One of the aims of the United Nations Environment Programme for sustainability is the protection of biodiversity [1]. This is emphasised through the mandatory requirement of Environmental Impact Assessments (EIAs) for certain constructions and through planning conditions. Developments such as wind farms require particular attention to predict the risk of turbines to flying fauna such as birds and bats. The highest risk of collision for flying fauna with man-made structures is at periods of poor weather and at night [2-5]. Nocturnal surveys carry as much as importance as diurnal surveys to establish potential risk [6].

Offshore locations and other similar environments can make manual surveys by personnel impractical [7]. The increasing growth of man-made structures in such locations makes remote surveys increasingly popular. Remote systems are incorporating motion or trigger based detection methods [8]. This helps reduce the analysis time required by personnel to analyse video data once collected by the remote system.

Depending on the type of the data required there are two commonly used remote systems in nocturnal surveying; radar-based and night-vision based. Radar-based systems are ideal for monitoring large areas. Night-vision based systems are better suited for more specified area surveying and offer species identification and flock analysis [7-8].

A number of computer vision methods are available for identifying and tracking target objects such as humans and cars. These are based on identifying certain features of a target, and then search for these features in other data sources (e.g. [9]). However, birds (and bats) are difficult to extract features from. Fauna that have freedom in all three dimensions tend to change shape rapidly whilst moving [10-11].

2.0 Detecting Wing Beat Frequencies

Distinguishing birds and bats from other objects that cause motion reduces analysis time. Rather than a spatial approach to classify bird and bat targets, the paper proposes the use of temporal target. Wing flapping is a unique descriptive feature of birds and bats. By analyzing this flapping motion temporally, it may be possible remove non-bird or bat activity, and classify species according to flapping pattern. This flapping motion is oscillatory, and can be described as either periodic (motion repeats over a constant time interval) or cyclic (motion repeats with a varying time interval).

2.1 Existing Periodicity Detection Approaches

As outlined above, it can be difficult to extract spatial features from birds or bats. A number of methods for analysing oscillatory motion have been reviewed in [12]. These methods are based on temporal analysis of motion, and look at how an object changes over time. Area-based comparisons of frames ignore spatial features and can be used on a variety of targets. Methods include Cutler and Davis [13], Plotnik and Rock [11] and Branzan-Albu et al. [14]. These methods are based on constructing a similarity matrix. Each element of the matrix represents the difference of a sequence of frames. Once the similarity matrix has been created, each method uses a different approach for determining periodicity. [13] and [11] use spectral power analysis to find the maximum power amplitude in the matrix. If the amplitude exceeds a specified threshold, the target is classified as moving periodically. [14] applies a number of image processing techniques such as thresholding and morphological operators to reduce the similarity matrix into a pattern along the identity diagonal.

[11, 13-14] rely on a number of cycles to identify periodic motion. In addition as bird and bat video clips can be very short (see below). Resulting similarity matrices will consist of few elements, and some feature-reducing image processing may fail.

2.2 Cyclic Motion Detection Using Similarity Matrices

Cyclic motion is defined in the paper as an action that repeats with non-uniform time intervals. This produces an intuitive pattern within a similarity matrix. A noise input into a similarity matrix does not produce such an obvious pattern. This is illustrated in fig. 1 using simulated data of 1D inputs over time.

It is assumed that high frequencies within a similarity matrix are likely to occur due to noise. Using a Fast Fourier Transform (FFT), the peak power amplitude frequency is found, and the image is smoothed after this amplitude using a low pass top hat filter. An Otsu threshold [15] is applied to the resulting image. A 3x3 Sobel edge detector is passed over the binary image. The greater the number of edge pixels in the final image, the less likely there is cyclic motion within the similarity matrix. This is shown in the rightmost column in fig. 1.

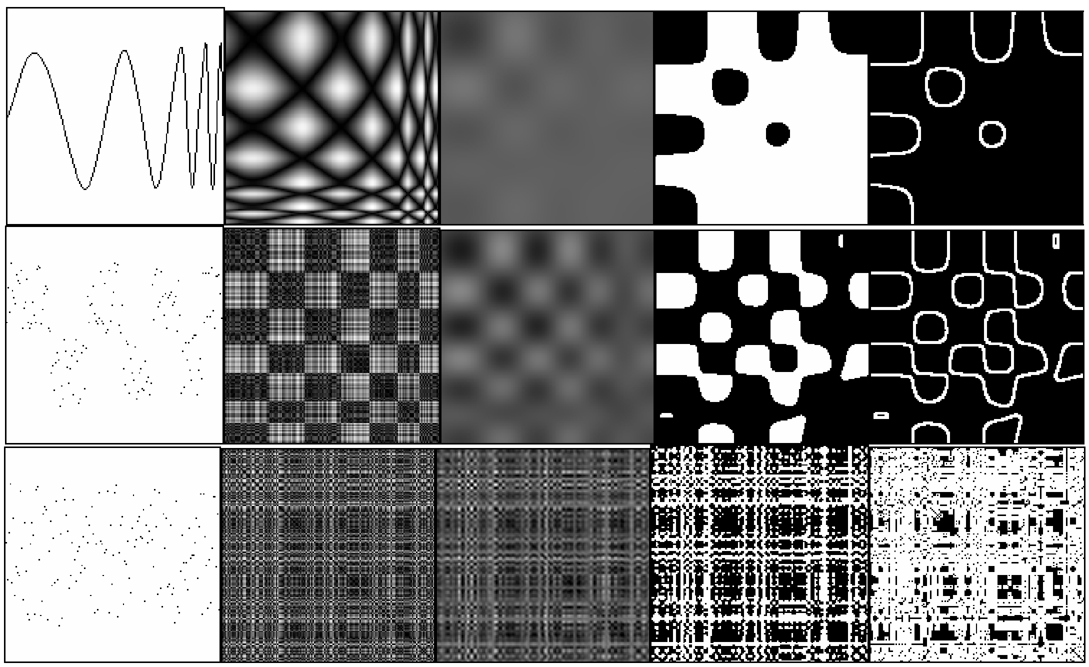

Fig. 1. Simulated data, associated similarity matrix and post-processing. From left to right, 1d simulated data, similarity matrix, low pass filter, Otsu threshold, Sobel edge detection.

For real data inputs targets are first segmented and binerised from each frame. Once segmented each object is aligned by its centre of gravity. The similarity matrix is calculated using

$$S_{t1,t2} = k\Sigma|O_{t1(x,y)} - O_{t2(x,y)}| \tag{1}$$

Where t1 and t2 represent the temporal periods between the aligned objects O, and S is the similarity matrix. A threshold value k (0.01 in this instance) is used.

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3.0 Identifying Specific Species

Identifying a specific species, or broader groups allows for further automation of bird and bat surveys. Automation can speed up analysis time of data, as well as alert operators to real-time situations that may require their attention. Using the cyclic motion detection technique outlined in section 2.2, the paper investigates whether templates can be generated from the method to identify certain bird species.

[13] uses lattices for identifying whether a target is either dog, human or other. A target similarity matrix is auto-correlated, and the lattices are fitted to the peaks. If there is a best match with either of the lattices, the object is classified as either dog or person. Otherwise the object is classified as other. A similar approach is used [11] for identifying gelatinous animals.

Birds and bats can cross a camera's viewshed quickly (typically one second or less – *pers obs*). With a video capture rate of 25 frames per second, there can be limited image frames available for analysis. This places a number of constraints on the methods available for identifying targets. For example, there may only be one or an incomplete cycle of flapping as the bird target crosses the screen. Also image processing techniques such as median filters may remove too much of a small similarity matrix. The use of the lattice technique used in [11] and [13] relies on a number of periodic cycles within the similarity matrix, which may not always occur.

Applying parts of the method outlined in section 2.2 to different flying fauna results in visually distinct similarity matrices as with the simulated data (fig. 2). Fauna are segmented using a running average (Heikkia and Olli) with threshold τ = 13 grayscale levels (8-bit images) 0.07, and learning rate α = 0.05 [16]. Flapping styles, rate of wing beat and soaring are visible within each of the matrices. This suggests that once processed, these matrices may be used as temporal templates for identifying species groups. The template may also not require a complete flap cycle.

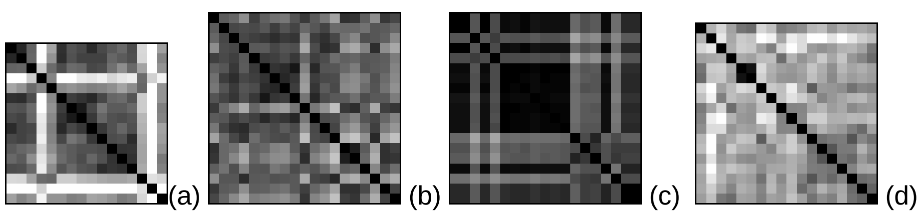

Fig. 2. Similarity matrices from flying fauna. (a) Bat. (b) Golden plover *Pluvialis apricaria*. (c) Harris hawk *Parabuteo unicinctus*. (d) Rook *Corvus frugilegus.*

3.1 Method Outline

Britain supports around 20% of the European Union (EU) population of Golden plover *Pluvialis apricaria* [17]. This large proportion places responsibility on Britain to conserve the population (Annex 1 of the EU Directive 79/409/EU) [18].

Using the Golden plover similarity matrix from fig. 2 (b) as a base, a section of the matrix encompassing a cycle was used to create the template (fig. 3). Targets are segmented from the video using the method outlined in section 3.0 except from the first Golden plover and the Rook clip which were segmented by hand. Targets segmented using the method in 3.0 were visually inspected to check that the target had been successfully segmented. Similarity matrices were generated from thermal infrared flying fauna clips using the method outlined in section 2.2. Fauna used were bat, Harris hawk, Rook, the original Golden plover event, and another Golden plover event. All of the video clips bar one were captured at 25 frames per second, sampled from previous survey video. One clip (the additional Golden plover clip) was at 29.97 frames per second. The resulting similarity matrix was scaled down by 20% to match the frame rate of the other similarity matrices. Each similarity matrix in turn was correlated with the template. All correlation points with a value above 0.5 were counted.

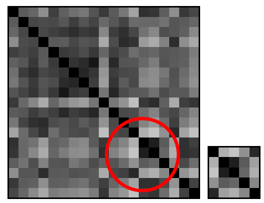

Fig. 3 The Golden plover similarity matrix used to create the template, and the template

4.0 Results

Peaks found within the correlated similarity matrices are shown in table I. A peak is defined as any pixel at or over the correlation value of 0.5 and any adjoining neighbouring pixels with this criterion. Hence, a peak can consist of one or more pixels.

Table I.
Summary of Results

Flying Fauna	Number of Peaks Over 0.5
Correlated with Self	11
Bat	3
Golden plover	6
Harris hawk	2
Rook	4

5.0 Conclusion

Similarity matrices offer a way of detecting periodic and cyclic motion. This is especially useful when rigid or constant features cannot be extracted from a target such as a bird or a bat.

The method presented in this paper for identifying Golden plover has had limited success. As expected, when the kernel was correlated with the original similarity matrix, the highest number of matches was found. The next highest number of peaks found was the other incident of a Golden plover. Other targets, however, also registered a number of peaks.

A number of factors may have restricted the approach. The relatively fast, cyclic nature of some bird flapping reduces the size of selectable templates, which can increase the likelihood of similar patterns appearing in other species similarity matrices. This could be addressed through capturing video at a faster frame rate. Differing greyscale colourings within the matrices will impact correlation results, even though distinctive features such as lines and squares may be 'overlooked'. As only one cycle is used as a template, there may be poor correlation with different-sized cycles elsewhere in the matrix.

There are similarities in shape within the matrices for both Golden plover examples. Two different instances of Golden plover flight are shown in fig. 4. Future work would be to determine how distinctive lines within matrices could be compared, rather than giving a high weighting to shading similarities. Also, how identification can be more flexible in identifying cyclic activity.

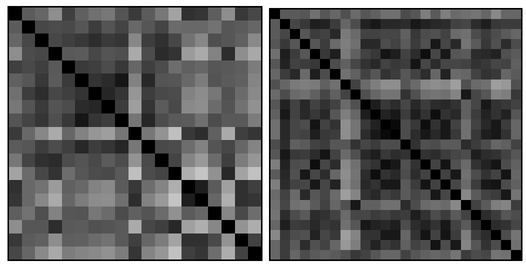

Fig. 4. Two instances of Golden plover flight.

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Appendix B: Determining Approximate Values for External Bird Temperatures

B.1 Background

Knowing the approximate difference between bird plumage and ambient temperature is useful for modelling bird targets in thermal imaging applications.

There is some, but not extensive, pre-existing literature that attempts to show a relationship between atmospheric temperature and bird plumage (surface) temperature (McCafferty *et al.* 1998, Phillips and Sanborn, 1994, Hill *et al.* 1980, Despin *et al.* 1978, Veghte and Herreid 1965). McCafferty *et al.* (1998) have produced a review of ambient temperature to surface temperature for a number of bird species (Table B.1). The relationship between ambient temperature and surface temperature is structured in the form of a straight-line equation, i.e.

$$y = mx + c \qquad \text{(Equation B.1)}$$

where y = surface temperature, m is the ratio between surface temperature and ambient temperature, x is ambient temperature, and c is a constant.

Species	Ta(°C)	m±SE	c±SE	R^2	Authors
Black-capped Chickadee *Parus atricapillus*	-22 to 27	0.79	8.6	-	Hill *et al.* (1980)
Black-capped Chickadee	-34 to 20	0.82±0.03	13.9±0.64	0.92	Veghte and Herreid (1965)
Gray Jay *Periosoreus Canadensis*	-37 to –8	1.01±0.04	12.7±1.04	0.91	Veghte and Herreid (1965)
White-tailed Ptarmigan *Lagopus leucurus*	-34 to –8	1.02±0.09	10.1±2.1	0.70	Veghte and Herreid (1965)
Raven *Corvus corax*	-41 to –8	1.18±0.07	10.8±1.9	0.83	Veghte and Herreid (1965)
Sharp-tailed Grouse *Tympanuchus phasianellus*	18 to 24	0.87	5.2	0.99	Evans and Moen (1975)
Barn Owl *Tyto alba*	5 to 25	1.04±0.03	1.3±0.55	0.98	Hamilton (1982)

Table B.1 Summary of the Relationship between Bird Surface Temperature and Ambient Temperature from McCafferty *et al.* (1998)

A large majority of the temperature values in the table are when the bird target is in considerably cold temperatures. As suggested by McCafferty *et al*. (1998), this may produce a larger difference in plumage temperature and atmospheric temperatures due to more heat being generated to prevent freezing. As it is unlikely that nocturnal surveys will be carried out in such cold environments the values given may not accurately reflect reasonable survey conditions. There is also likely to be a variance between the ambient-surface temperature relationship and bird species, with some species being better insulated than others.

In order to gather more information at temperatures most likely encountered in nocturnal surveys, further bird temperatures (geese) and ambient temperatures were collected.

B.2 Method

Using a FLIR ThermaCam P60 thermal imager, sample images of wildfowl were taken. The wildfowl were approximately 2-15 m away from the camera. For reference, images of grass-covered ground were taken, also 2-15 m away from the camera. The thermal imager was either mounted onto a tripod or carried to capture images of the wildfowl. For each image captured, the camera was focused onto the nearest wildfowl to the camera. Images were stored as radiometric JPEGs. Images were captured at two different points during the same day. In the morning there was light rain, and in the late afternoon there was strong sunshine, with past areas dried from the earlier rain. A total of 7 images were captured during the rain and 23 pictures during the sunshine. Grass was used to assess ambient temperature as it will have been exposed to the ambient temperature for long periods of time, and is typical of the surface one would expect to see a wildfowl against. Once collected, the images were assessed in FLIR ThermaCAM Reporter Pro (2000). A temperature analysis box was placed over a number of the wildfowl, and the peak temperature for each wildfowl and grass section are used. For measuring peak grass temperature, an analysis box was randomly placed over five different areas of grass.

B.3 Results

Maximum temperatures of all geese during rain, geese during sunshine, grass during rain and grass during sunshine were collated together to find the mean average and standard deviation. Sample numbers along with results can be found in Table B.2.

Description	Number of Samples	Rain/Sun	Peak (°C ±SD)
Goose Sp.	23	Rain	16.0 ±1.6
Goose Sp.	36	Sun	27.9 ±2.5
Grass Samples	40	Rain	9.4 ±0.5
Grass Samples	80	Sun	22.2 ±0.6

Table B.2 Summary of Temperatures

The temperature difference between geese and grass during rain was 7.2°C. The temperature difference between geese and grass during sunshine was 5.1°C.

B.4 Discussion

Based on the limited literature that could be found, there is a relationship between ambient temperature and surface temperature. It suggests that the difference between surface temperature and ambient temperature increases as ambient temperature decreases, and decreases as the ambient temperature increases. There was no specific value for birds as a whole. This is attributed to different insulation properties of different species. It was also felt the significantly low temperatures birds were kept at would provide misleading values.

Collecting data from both periods of rain and sunshine has provided a guide bird surface-ambient temperature difference of 7.2°C and 5.1°C. During sunshine the overall temperatures for both grass and geese were significantly higher than in the rain. The smaller difference in surface to ambient temperature was likely due to this. The temperatures obtained can be used as an indicative guide for how much heat simulated bird targets should produce.

Appendix C: Target Construction

C.1 Introduction

A total of nine targets were made to represent a number of factors one would expect field ornithologists to encounter during nocturnal bird surveys. These factors were: size, shading, shape and eye-shine. As a thermal imaging camera is also being used, three of the targets were also heated.

Size: small (15cm) to represent waders such as Dunlin, Golden plover, medium (35cm) to represent duck such as Pochard and Tufted duck, and large (50cm) to represent geese such as Pink-footed and Greylag geese.

Shading: light, medium and dark.

Shape and eye-shine: the targets were of identical shape, each having an arrowhead. Eye-shine was also simulated as this is used in target detection.

Heating: the targets were designed to try and maintain a 5°C difference above ambient temperature.

C.2 Non-Heated Targets

All of the targets were made out of polypropylene carpet tiles. All of the targets were cut to 15cm, 35cm or 50cm squares. An arrowhead was cut out in all of the targets. The proportion of the arrowhead was set at 1/3 of the length of the side. A reflective button was attached to the targets to provide reflective eye-shine. The button was placed 1/3 by 1/3 of the length on the same side as the arrowhead. Figure C.1 shows one of the constructed targets, and Figure C.2 shows the different shades.

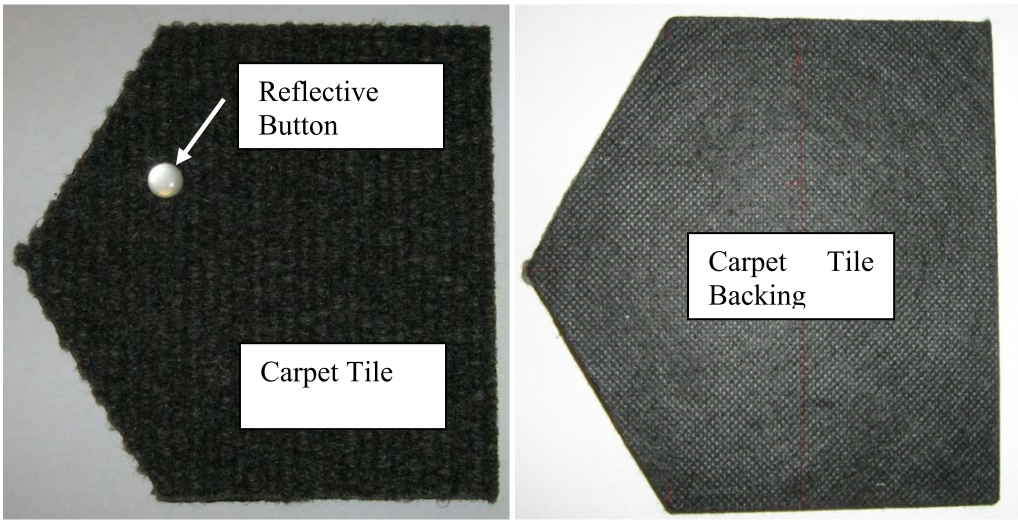


Figure C.1 Non-heated decoy

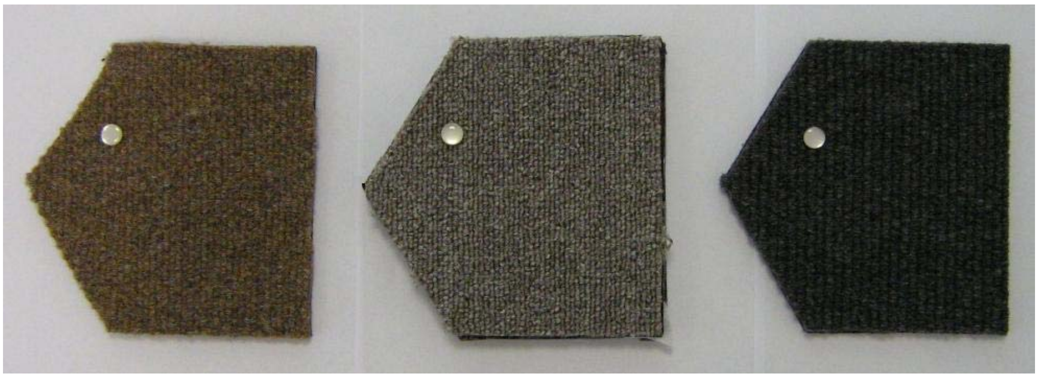


Figure C.2 Target shades

C.3 Heated Targets

The lightest coloured targets were chosen at random as the heated targets. Matching sized target shapes were cut out of galvanised aluminium sheeting, aluminium foil and insulating polystyrene sheeting. The aluminium sheets were then attached to the carpet tile backing using doubled sided tape. The polystyrene sheets and aluminium foil were joined together with doubled-sided tape, and the back polystyrene sheet was covered with gaffer tape. The two parts of the target are hinged together with gaffer tape. To enable different heating systems to be placed within the decoy, Velcro hoops and loops were placed around the edge of the decoy to allow easy access (Figure C.3).

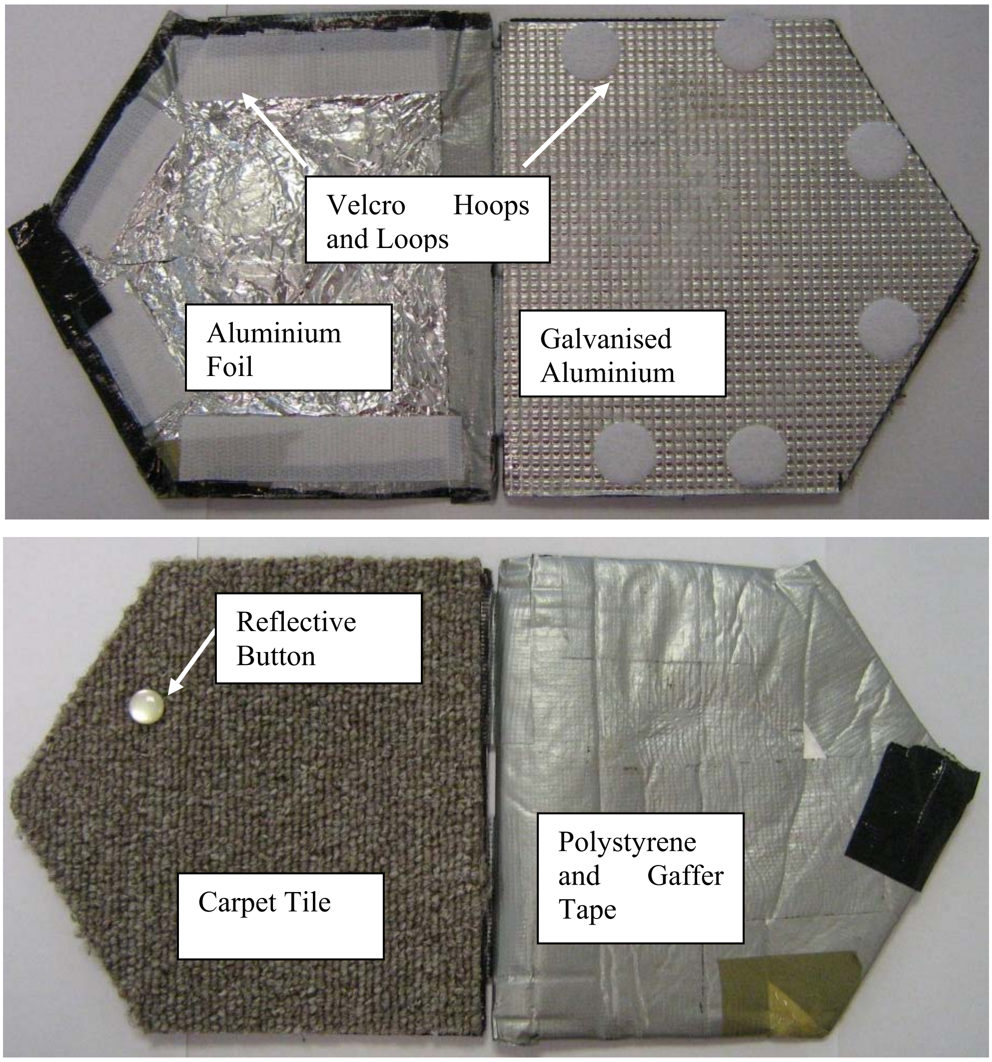


Figure C.3 Internal and external view of heated target

Two different heating systems were used to heat the targets, one for the smallest decoy, and another for the two larger targets. For the small target, four 6.8Ω 11W ceramic-coated wire wound resistors were placed in series. Insulating tape was wrapped around the solder joints, and around the crocodile clips connecting the leads to the resistors (Figure C.4). Total power output from the resistors is 5.29W from a 12V direct current supply. Greaseproof paper was placed on either side of the decoy to reduce the likelihood of a short circuit. The resistors are held in place by closing the target sides.

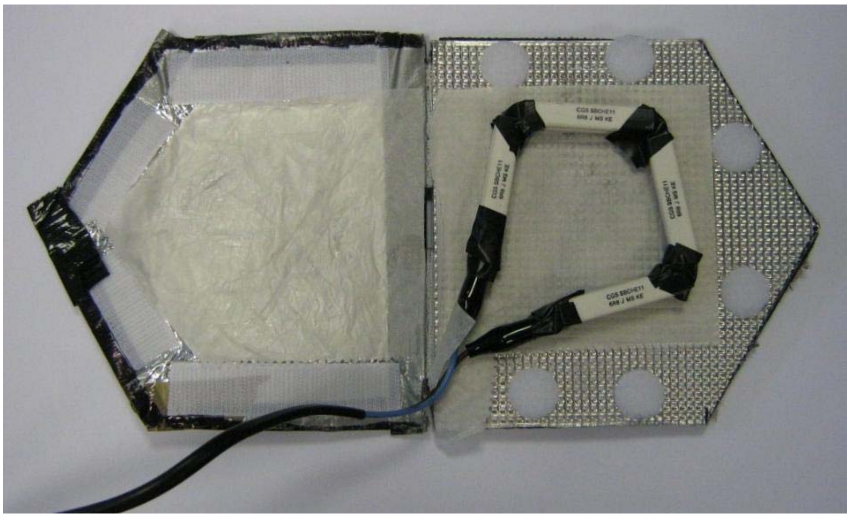


Figure C.4 Resistor network with insulating grease-proof paper

For the medium and large targets, a portable cooker (Cookworks Double Boiling Ring) was disassembled and the large and small heating plates were removed. The resistance of the plates were measured using a multimeter (Mastech M-830B). The large plate (18.9cm diameter) was measured 36.6 Ω. The small plate (14.3cm diameter) 53.8 Ω. Total output power for the small plate is 10.7W (24V direct current supply). Total output power for the large plate is 15.7W (24V direct current supply). The plates were attached to the targets using gaffer tape, directly taping the plate to the aluminium side of the target (Figure C.5). To improve the insulation of the back of the target, an additional piece of carpet was added to the polystyrene backing. To reduce the likelihood of short-circuit, the aluminium foil was removed.

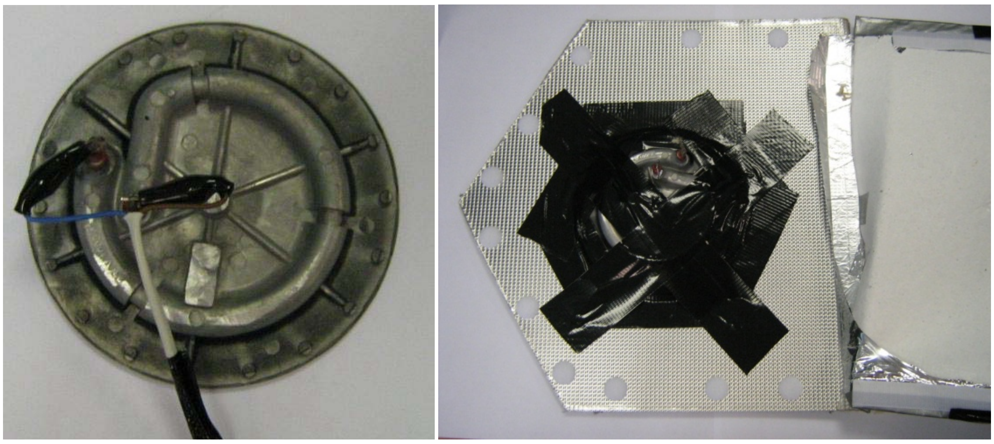


Figure C.5 Heating plate exposed and heating plate attached to target

An alternative heating system was designed for the medium and large targets, based on the small target due to some issues that arose with heating-plate based system. As with the small target, four 6.8Ω 11W ceramic-coated wire-wound resistors were placed in series. Insulating tape was wrapped around the solder joints to reduce the risk of short-circuit. For the medium target, four of the resistor set-ups were used, and connected in parallel by bell wire. For the large target, nine of the resistor set-ups were used, connected in parallel with bell wire. The resistors were taped directly onto the aluminium side. The arrangements of the resistor set-ups are shown in Figure C.6.

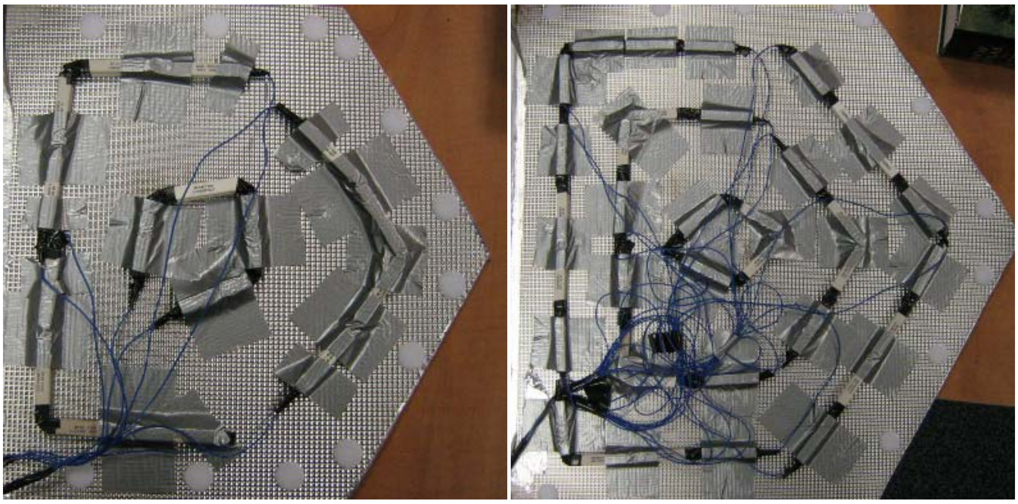


Figure C.6 Resistor set-up layouts for medium and large heated targets

C.4 Results

Initial trials suggest that the heating systems work and provide approximately 4-6°C difference above ambient temperature. The resistor network for the small target appeared to work very well, with heat spreading across the whole target. The targ*et al*so resembled a heat image associated with seeing birds with a thermal imager. The heating plates were effective to a degree, but heat distribution is concentrated at the centre of the target, and does not spread as well as with the small target. The new heat system for the medium and large target produced more favourable simulated bird targets, mirroring the small target.

C.5 Conclusion

Nine targets for field-testing have been created. The original heating-plate based system for the medium and large targets did not work as well as expected. Replacing the heating plates with a resistor-based system as used in the small target functioned significantly better.

Appendix D: Interview Transcripts

D.1 Overview

This section provides the transcripts collected during the interviewing of the ornithology surveyors. All interviewee responses are bulleted.

Any mentions of nightsight and Cluson refer to image intensifier and infrared lamp respectively.

D.2 Transcripts

Alan Bull (13/08/08)

What surveys have you been involved in, both with RPS and other organisations?

- Coventry Farm
    - Organised and designed methodology
- Tilbury
- Alaska
    - Not involved with any of the work
- Coventry Farm
- No nocturnal work outside of RPS

Why was thermal imager was not chosen?

- Limitations of survey area
    - Assessing flights
    - Range of camera too low
    - Fixed position too limited
    - Nightsight offered more freedom
    - Camera covered smaller percentage of viewshed
    - Not sure about Golden plover activity
    - Need to assess collision risk during night
    - Not used for collision monitoring
    - Need to know what birds were doing
    - Flying?
    - Feeding?
    - Activity?
    - No need to concentrate effort.
    - Cost was high for a scoping/sampling survey

Do you know that you can move the camera and pan/tilt?

- Unsure of free movement with camera
- Unsure of camera usage

What do you consider to be the strengths and weaknesses of the image intensifier?

- Against clear sky (no Cluson)
  - 1-1.5km in full-half moon (eared-owl)
  - 600m wood pigeon
  - 1-off situations
  - Against ground (no Cluson) (Except dusk and dawn)
  - Range of up to 50m
  - Full-moon up to 100m at some vantage points
- Against clear sky (with Cluson)
  - No difference
- Against ground (with Cluson)
  - Big difference
  - For crop 0-7 inches high
  - Most situations up to 200m
  - Best situation is when the land is sloping down away from the surveyor, up to 400m

What about moon?

- For crop higher than 7 inches
- Cannot see targets on ground
- Light pollution
- Cambridge in background – range dropped down to 70m (no Cluson).
- Traffic (site has A14 and A10 passing by) may have improved target detection – owl spotted by being illuminated by a lorry headlamp
- Rain
- Not used enough in rain to make firm comments – opinion – not usable in rain
- Nightsight also steams up in rain
- Identification
- Very few species on site, mainly Golden plover and Lapwing which were easy to id (for an experienced ornithologist)
- Owl identified mainly with JIZZ, wood pigeon identified mainly by shape
- Birds on ground – scan for eye shine

Describe the Tilbury survey

- Tilbury
- Shoreline counts
- Just night sight, no Cluson used for additional illumination
- Walked up and down the shoreline and counted waders in high and low tides
- Surveys always done in ideal conditions

Can you describe the site?

- Lot of light pollution
- Area with no light – couldn't see any birds
- Area with light – picked up most birds up to 200-300 metres
- Light helped a lot

How did the moon affect what you saw?

- Moon also helped
- Mud was wet – appeared shiny – not sure if this was the case at all times

How did you identify birds?

- Mainly done with JIZZ, with some shape
- Knowledge of what birds were doing and their behaviour during the day helped identify them during the night

Describe your knowledge of the Alaska survey

- Brief encounter with thermal imaging in Alaska
- Nothing to see, so difficult to comment

What awareness do you have of other nocturnal surveys?

- Night sight telescope – unsure of details used – range of 400-800 metres
- Friend used a night scope to watch leaches petrels going in and out of burrows.

What are your personal opinions of the limitations of the image intensifier?

- Range
- High crops
- Grainy image without Cluson
- Unable to use equipment in rain
- Might miss birds as it is difficult to identify whether stuff is being missed
- Can only use the nightsight in 10 minutes in succession before passing it to a colleague (3x10 minute samples each per hour)

What about other weather conditions, such as fog?

- Opinion is that it will not be useful in fog

What are your opinions of the limitations of the thermal imager?

- Not much experience, but...
    - Range
    - Depth of field – difficult to tell whether small object near camera or big object far away. Difficulties in differentiating between insect, bat, bird
    - If camera is fixed, only a limited range/viewshed is available
- For video clips...
    - Difficult to differentiate some birds
    - Heat trail left behind can be confusing
    - Don’t think it is a useful tool

Any other limitations such as installation?

- Equipment potentially heavy if full set up (computers, batteries, etc) are required for survey

What improvements to thermal imager would you like to see?

- Having some sort of distance reference would be useful
- Understand some basic rules for the camera

If you were in the position to choose equipment for surveys involved, what would you have selected?

- For Alaska, based on flight lines and number of targets spotted, night sight
- For Coventry farm, night sight, as survey was carried out
- For Tilbury, a trial of the thermal imager would be useful – especially in areas where potentially birds may be missed using the night sight.

Anything else you would like to add?

- Methodology for Coventry Farm

Additional Documents Supplied
O:\JPP1796 Coventry Windfarm\Scoping surveys for nocturnal GP at Coventry Farm.doc

Andrew Seth (18/08/08)

What nocturnal surveys have you been involved in, both within and outside of RPS?

- Night in Besborough
- Abberton
- Tilbury
- Stonish
- Bleak House
- Alaska
- Coventry Farm
- Carscreugh (when prompted)
- No survey involvement outside of RPS

Describe your work in Night in Besborough

- Two small reservoirs
- Wildfowl count – walking around reservoirs
- Over two winters, 2 visits per month over winter – although only did a couple of visits for the first winter as had only recently started at RPS
- Weather – dry and clear "ideal weather conditions"
- A fair bit of light from surrounding street lights
- Lights behind the nightsight provided additional ambient lighting which helped in the field.
- Lights in front of the nightsight impedes seeing objects. Looking at water with lights close by made it difficult to see birds. So looking at water with lights close by opposite makes it difficult to use the nightsight.

How did you overcome this problem?
- The best way to resolve lighting problems such as this is – change the angle at which the area is being observed so that lights run perpendicular to the area being scanned.
- Difficult to id targets without Cluson with nightsight

What about affects of moon?
- No moon – cloudy night harder to see

What about other weather effects?
- Any drizzle – harder to see
- Affects nightsight by putting a fine haze across it
- Appears to shut out light

What would you consider to be optimum conditions?
- Decent size moon – half to full
- Dry
- Clear – not misty, low/no moisture
- Still – if windy – makes shapes harder to identify (birds identified by shape, jizz and behaviour)
- Tripod a big advantage

Describe your work at Abberton
- No Cluson was used
- Big site – distances beyond range of nightsight
- Previous staff, CM and IE appeared to have a lot more experience using the nightsight
- Open areas – more problems with weather conditions, esp. wind
- No way to record all birds at night
- Too many dark areas
- Shadows of trees hide birds

Describe your work at Stonish using the image intensifier
- Good for scanning for Nightjars and owls
- Hard to see in woodland
- When grass is taller and lighter it is easier to pick objects up
- Much easier to see stuff with Cluson
- No guarantees to pick stuff up for negatives (i.e. there is no presence)
- Hear birds calling and then try to find them with nightsight
- Not sure if using a nightsight to see if NJ are foraging (or Thermal)
- Prime time for Nightsight is 2-3 hours after sunset and 2-3 hours before sunset when there is some light
- Pitch black are worst conditions

Describe your work at Carscreugh
- Foggy, low cloud, damp, cold

- Cannot remember if they used a nightsight
- Thermal imager
- Couldn’t see much
- Don’t remember much about the survey

Describe your work at Bleak House with the image intensifier and the thermal imager

- Thermal Imager - Constant height, probably alternating height might have been better – depends on question being answered
- Limitations - Identifying targets – narrow field of view, not enough depth of field
- Getting the colours and range right to detect stuff – colours used possibly too bright to see detected targets

What weather conditions was the thermal imager used in?

- Good weather conditions – stopped recording during showers

And the image intensifier?

- Light conditions at Bleak House good for Nightsight, doesn’t affect thermal imager
- Keeping the thermal camera in same positions may be limited, maybe be a better system to scan from side to side

What would you consider to be thermal imager advantages and disadvantages?

- Always recording
- Not relying on human to keep concentration
- Constant observation throughout the night (pros come with ID)
- Good range – detect range 300-400m, ID range 150-200m
- Able to pick stuff up in the sky in the dark, especially when it is really dark – may be difficult to pick up something in the sky with NS – easy with thermal imager
- Nightsight difficult against dark background
- Narrow field of view will pick less flights
- Uneven ground may limit walking around with thermal imager – not as portable as nightsight/fear of damaging expensive equipment
- Moving TI around could help improve surveys
- Maybe more suitable to use 2 cameras, one in a fixed position and one moved around

Describe your experience at Alaska

- Similar to Bleak House
- Not as much street light as Bleak House
- Could get darker
- More Nightjar about, bats, gulls

In what situations would you consider one piece of equipment better over another?

- Nightsight better choice over thermal imager (using a Cluson) for presence/absence surveys
- Where more quantitative data is required, such as for collision risk, and where height information is required, a similar set up to Alaska, using a thermal imager in combination with nightsight is a good system.
- Cluson picked up more birds at Alaska than without for nightsight
- Hard to tell whether bird flights drop off during the night with Nightsight – quiet during 11-2.

What would you suggest to improve thermal imager usability?

- Calibrating camera
- Weather details
- Range associated
- Trying different range
- Trying different colours
- Colour ranges – automatic may not pick best colours – manual needs to be monitored overnight as environment cools down

What limitations would you associate with the image intensifier?

- Much like what has been discussed
- Nightsight limitations (Coventry farm)
- Didn't work will in sky
- Good for counting birds on ground
- Most activity at dusk and dawn. Still with some light
- Good in short crop
- Without Cluson up to 200m
- With Cluson 300-400m

So you are suggesting that the thermal imager and image intensifier have similar ranges?

- Similar range to detect targets with thermal imager and night sight
- What distances do you need to identify a target?
- To identify targets with nightsight on ground no Cluson 100-150m, with Cluson, 300-400m
- If target flying, 50-100m with Nightsight
- Unless really good light
- Can detect stuff further away but hard to identify
- Possibly down to family

What weather conditions limit the use of the image intensifier?

- Mist, rain, fog, heavy drizzle, extreme wind
- Cold may steam up lens (towards zero degrees)

Describe your experience at Tilbury

- Half of site reasonable to see
- Easier to see targets on mud

Why were the targets easier to see?
- Shiny mud helped reflect light
- Cluson would have helped
- Try to work with lights – power station lights helped
- High ID rate – no high distances involved
- Nightsight uses little energy – cheaper to run

What landscape profiles work best for image intensifier?
- Best to look across than down hills
- More skyline in nightsight the better
- But depends on what you are looking for
- Against woodland hard, open fields better

What landscape profiles work best for thermal imager?
- Land helps give perspective of distance
- Too much background clutter can make it difficult to identify targets
- Not sure about woodland/fields effect for thermal imager, more work is required to compare.

Can you think of anything else that needs to be added?
- No

Rob Martin (04/09/08)

What nocturnal surveys have you been involved in, both within and outside of RPS?
- Bleak House
- Alaska
- Lanarkshire
- South West London
- Abberton
- Tilbury
- Coventry Farm

What non-RPS nocturnal surveys have you been involved in?
- No nocturnal surveys that can be recalled
- Searching for birds and mammals at night, but with no night vision equipment

Describe the Bleak House survey
- Determining the presence/absence of Nightjars
- Didn't know if Nightjars are using the site
- Setting the thermal imager across certain parts of the site

- Mostly felt that night sight had a chance of picking stuff up
- Nightjar picked up on night sight (but not by Rob), by Nick Askew
- No Nightjars picked up by thermal imager

Describe the survey site
- Old mine, acid based, arable farmland, recovering heath land
- Hill, gentle hill, undulating

Describe the weather conditions encountered
- Can't remember, details are on survey sheets
- Had to stop for a bit, due to some rain
- Difficult to remember

What about the moon? How did it affect equipment?
- Didn't notice
- No consideration for moon
- Only 3 visits
- In general (not specific to Alaska) moon can make it brighter, easier to see. Moon obscured by clouds also makes it dark as with no moon.

What was your general opinion of the survey?
- If Nightjar using site, more likely to see with night sight
- Felt less likely to pick them up with thermal imager
- If just using thermal imager, wouldn't be happy to say absence of Nightjar
- Use of multiple vantage points with night sight meant a lot more of the site was covered – feeling of picking up Nightjar
- Site appeared mostly not used heavily by Nightjar
- Difficult to prove presence, no calling or singing on site

So if using night sight alone, you would be happy to conclude presence/absence?
- Yes – perhaps supported by more visits

Did you feel there was benefit in having the thermal imager there?
- Because we were surveying throughout the night with the night sight, it was hard to see how to pick up more
- When looking for presence/absence information, if a Nightjar was picked up with a thermal imager, you would be more than likely to see it with the night sight
- The survey was not looking for flight heights or passes, so thermal imager was surplus to requirements.

Any other thoughts on Bleak House?
- Carting equipment to vantage point was a problem
- Not a big issue, but took longer to set up

Describe the Alaska survey, purpose of survey, etc.

- Small wind farm site
- Surveys to determine how site is being used by Nightjars
- How Nightjars are around turbine locations
- Initially looking at numbers and activity, but survey methodology changed
- Greatly improved by making more focussed assessments

What were these focussed assessments and how did they improve things?

- Started using different height bands with the thermal imager, at which records of Nightjar heights may be of significance (e.g. at rotor height) rather than prove Nightjar are at site
- Easy to monitor Nightjar presence with night sight, but thermal imager gives some way of monitoring a certain height with respect to environmental statements, whereas with night sight you tend to focus on picking up nightjar lower down, more difficult to pick up flying higher up – so might miss flights at higher altitudes – OR may prove nightjar not flying at higher altitudes.
- Very difficult to assess height with night sight as it produces a flat image
- Infrared lamp greatly increases likelihood of picking up nightjars at greater distances
- Thermal imager present in a location and looking over location in a measurable time. A couple of flights may be caught by thermal imager than night sight, but this could be remedied by increasing effort with night sight.

What weather conditions did you experience?

- Usually reasonable, occasionally abandoned survey due to rain. Can be very windy. Quite a variation in weather, warm/cold, moon/moonless
- Relevance of weather – may have to stop survey. Poorer weather may mean less likely to see nightjars as they are less active in poor weather conditions

Describe the survey site area

- Quarry, rolling hills, heathland

What were your thoughts on the survey? What would you change?

- Thermal imaging had a place – it was of use
- Trying to record stuff at higher heights. Still not sure about how much of site is covered, and how it can be related to activity
- Night sight better at assessing general nightjar activity
- Needed external hard disk and better laptop to record data
- Better connections on leads – sometimes leads would not connect – forced to change timings to failed recordings
- Laptop very slow
- Better to be able to record directly to external hard disk.

Any other thoughts on how survey could be improved?

- The value of the data – what can be said with the thermal imager is low
- Limitations on statements that can be made
- Surveying very small area of sky at any one time
- Pointing at turbine airspace to look at collision risk
- Because of small field of view, can only point at small section of airspace of turbine sweep – unlikely to have many flights
- Tenuous to scale up flights to represent whole wind farm
- Need more hours to have more confidence/statistically – but this is costly!
- Biggest drawback is field of view
- Also better image to identify targets – not passing off insects, etc as nightjars
- Big 180° sweet with night sight
- You have a situation of situation of turbine airspace sample for 180° sweep (night sight) verses field of view sample of turbine airspace (thermal imager)

What range for Nightjar – the trade off between magnification and field of view for thermal imager?
- Hasn't been assessed
- Need to have some confidence, e.g. at up to 50m we can identify nightjars
- Wider field of view means more likely to spot stuff – but identifying may be harder – but object takes longer to go through field of view
- Literally relying on flight style to identify a dot
- Can use night sight as binoculars, harder than binoculars at times. Sweep around, feel like you will pick more stuff up

Are thermal imager and night sight complementally or do you feel thermal imaging is redundant?
- Night sight has a more wide-ranging use
- More adaptable, but with some limitations
- There is a direct interpretation of a scene with an infrared lamp. You can get a very good assessment at night
- Thermal imager better for applications where you have to monitor a specific location remotely
- Situations where massive amounts of data collected is impractical to expect a human to look through a night sight.
- You pick up things you wouldn't with a night sight – but sampling resolves this
- If you need to locate everything at a specific location, then thermal imaging is good
- If you are assessing a site, night sight is good

Describe SW London and Abberton surveys
- Cannot see application for thermal imager at either site
- Cannot identify stuff with thermal imager

Describe Lanarkshire surveys

- Trialling equipment to look for pink-footed goose
- Thermal imager very good for picking up geese than night sight
- Good for remote applications where looking for big things
- The thermal imager excels where identification is not important, such as when you have prior knowledge what is present
- When interested of effects on particular species, especially where other species are present, thermal imaging not so good

Describe Coventry Farm surveys

- Night sight was pretty capable of detecting Golden plover, especially with infrared lamp
- Perfectly adequate methodology
- Difficult to incorporate thermal imaging into set up where data would be in support of an assessment
- Thermal imager let down with field of view
- If trying to locate animals in cryptic environment (such as a ploughed field) the thermal imager is good because it detects heat.
- If you know what species are involved thermal imager quick to pick stuff up

Describe Tilbury Surveys

- Not able to identify birds with thermal imager
- Maybe more likely to pick up more individual birds, but not necessarily identify them
- Night sight range of around 400m
- Night sight best choice for this survey

What do you consider to be the advantages and disadvantages of the image intensifier?

- Range of equipment
  - No moon, no light – not likely to see much
  - No moon, with infrared lamp – 200-400 metre range
  - Bright moon – if looking towards moon – difficult as shadows casts, but away from boon can see at great distances
  - Use infrared to pick up eye shine
  - Bright lights can give shadows
- Weather
  - Misty (visibility 50m) can see very little
  - If raining range of 50-100m (infrared lamp makes less of a difference), lot of reflected light off rain when using infrared lamp
- Ideal conditions (dry, full moon, infrared lamp)
  - Up o 400metres (infrared lamp helps pick up eye shine)
  - Depends on background. Dark background (such as a ploughed field) makes it very hard to see
  - Ploughed fields are the worst
  - Holds up to weather ok

- Advantages
    - Portable
    - Can be used as binoculars are during the day to scan an area for bird activity as you can sweep around you feel as though you will pick up more targets.
    - Can give reasonably accurate assessment
    - Not so expensive
    - Simple to use
- Disadvantages
    - Limited by atmospheric conditions
    - Slightly awkward to using infrared
    - Smaller field of view compared to binoculars or a scope
    - Some difficulties in picking up bird at height in flight
    - Would be easier if light was mounted on night sight
    - Glare affects equipment sometimes

What do you consider to be advantages and disadvantages of the thermal imager?

- Range
    - Difficult to tell (a disadvantages)
    - Rely on speed of object to assess
    - No depth perception
    - Difficult to differentiate objects
    - Easier to identify larger objects, such as ducks, geese, cranes and waders
    - Small birds not so good to identify
- Advantages
    - Picking up things that are of reasonable size
    - Picking up things that you otherwise wouldn't see
    - Fixed at a location and retrieve data later – don't miss things
    - Associated software
    - Good for geese and other large species migrating at distance
    - Good for confirmed Golden plover over a considerable range
    - Point specific applications – better than sitting in a fixed point with a night sight – would go mad having to watch the same point with a night sight for 6 hours continuous
- Disadvantages
    - Limited field of view
    - Difficulties in identifying small targets
    - Identifying targets to species level
    - Transporting equipment
    - Can't use it as a scanning device
    - Difficulty in detecting distance – errors associated with distance

Any other thoughts?

- Assessing a site – use a night sight
- Point location that needs to be monitored for long periods of time – use a thermal imager

Appendix E: Equipment and Surveillance Information

E.1 Introduction

A number of factors, such as camera resolution, typical observed scenes and target under surveillance could affect what computer vision techniques are used when working with video data.

This section provides details on such factors that were grouped into related categories. This information was been gathered from manufacturer sources, literature, and user experience from the equipment in survey situations.

E.2 Equipment Information

As the thermal imager is always used for fixed vantage point surveys, and not used for scanning, as an image intensifier would be, the thermal imager always remains stationary.

The thermal imager used is a FLIR P60. The field of views used on it are either 24° (built in lens), or 12° (attached lens). The 12° lens is the most likely to be used for medium to long range views (50-400m). The pixel spatial resolution on the P60 is 320 by 240 (FLIR Systems 2002). Thermal imagers work on a false colour system, where colours or greyscale intensities are used to represent different detected temperatures. These colour values bear no relationship with visible colours and any similarities are coincidental. Image frames output by the P60 are 256 RGB colours or greyscale levels. The PAL output of the P60 is used to gather the video data. A USB digital frame-grabber (ADS InstantVideo) is connected to the analogue video output from the P60 and to a laptop. Video is typically stored as MPEG at 25 frames per second, using a resolution of 640 by 480.

Large stationary objects, such as buildings may cast viewable ‘shadows’ on the ground, viewable by a thermal imager. These perceived shadows are due those areas of the ground being shaded by the building for sufficiently long periods of time to physically cool the ground, hence creating the shadow (Bastian 2004). As flying fauna move across an area, any shadow that would be visible using a conventional camera based on the visible light spectrum would not be visible by a thermal imager. Using this same principle, sudden ambient illumination changes that occur from changes in cloud cover would not generate such visible differences with a thermal imager. A thermal imager will detect changes in scene temperature, such as those from the ground cooling during the evening, or gradually heating from dawn to day. These changes in scene temperature tend to be slow, gradual changes, rather than sudden events.

E.3 Survey Area Information

Generally, a thermal performs best at a vantage point where there is an open, uncluttered background, and is most useful in nocturnal bird surveillance when monitoring airspace. Used in this way, occlusions from other moving objects and interference from individuals in the camera's field of view is unlikely. From previous experience, it has been observed that due to the low resolution of the thermal imager, distant flora, such as trees and hedgerows, tend to be too distant from the camera's vantage point, for wind shake to cause visible motion, should airspace not be primarily observed. Strong winds have been observed to cause fast-moving clouds on occasion.

Overall, the scene over which a thermal imager looks over for nocturnal bird surveys are typically calm and still, with the majority of motion occurring from fauna notion, accidental surveyor motion, or from exceptionally fast-moving clouds.

One key scenario that differs from above is when the need arises to monitor airspace with wind turbines present. If the thermal imager is set up to monitor a wind turbine, continual motion from rotating turbine blades is present in the imager's field of view.

E.4 Surveyed Flying Fauna Information

Birds are not the only fauna likely to be detected by a thermal imager. If the imager is overlooking an open scene, past surveys have shown that voles, rabbits and deer have also been detected. If the imager is surveying airspace, bats and insects have also been ascertained.

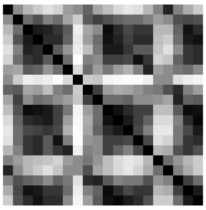
Depending on the lens magnification used, a fauna target can be detected with a thermal imager over many hundreds of metres. Field trials results in Chapter 3 show the thermal imager with a 12° lens detecting targets representing duck and goose-sized targets to at least 300 m. Surveyor experience from past surveys show detection ranges of some 400 m. The number of (spatial) pixels to represent the length of a bird target can vary, depending on the size of the bird, the distance it is away from the camera, and lens used. Based on the Johnson's Criteria for detecting targets (Johnson 1958), a surveyor can visually detect a target two pixels in size. Hence any automated system needs to detect targets of this size.

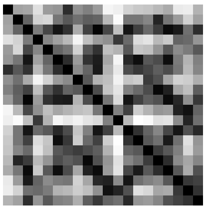
The thermal imager can be used to monitor different species of birds when used for fixed-point bird surveillance. This removes any prior knowledge related to the species families and number of birds likely to be moving in and out of the imager's field of view. There could be a solitary owl on a hunt, a pair of ducks flying in to land at a body of water, or a flock of geese moving off to roost.

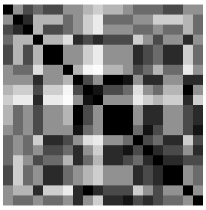
E.5 Summary

An overview of the factors to consider for automating nocturnal bird surveillance video using a thermal imager has been provided.

Appendix F: Perception Test Sheet

1 

2 

3 

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