Debugging Bat Tracking on a Central Iowa Wind Farm: Support Vector Machine for Flying Object Classification

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ABSTRACT

Wind energy development can threaten migratory species of bats, due to often fatal collisions with turbines. Estimates of fatalities at facilities in the United States were placed at 15.3-41.1 bats per megawatt of installed capacity per year. Thermal cameras used to track bat activity often capture other objects, namely flying insects, that are indistinguishable from bats in the footage. Thus, I attempted to use Support Vector Machine to sort objects on a central Iowa wind farm into two domains – one for each class. Using the objects' reconstructed flight tracks, I found that one class generally had 50 or more points per track and a value of 5-10 for distance between points, which I suspected were bats, while the other class had 40 or less points per track and a range of 5-30 for distance between points. Additionally, I found that shutting down turbine operation at low wind speeds has shown success at reducing bat fatalities by approximately 60%. My results could be used to sort flying object tracks in the future based on their location in one domain or the other, and improve the efficiency of bat tracking and mitigation.

KEYWORDS

supervised learning algorithm, wind energy, machine learning, object identification, bat fatalities

INTRODUCTION

As the effects of climate change increasingly threaten the fate of the planet, energy production is shifting its focus from fossil fuels to more eco-friendly sources, collectively known as “renewable energy”. One form of renewable energy with high potential for offsetting greenhouse gas emissions is wind energy. Structures called turbines use wind power to generate energy for a variety of purposes, such as powering windmills, pumping water, or sailing boats (Şahin 2004). These typically take the form of horizontal-axis turbines with three blades, though two-blade designs are also common (Tong 2010). However, wind energy can negatively impact biodiversity, as bats and birds get injured or killed in collisions with turbines. At wind energy facilities installed along forested ridgetops in the eastern United States, it was estimated that 15.3 to 41.1 bat fatalities occur per megawatt of installed capacity per year, with migratory species especially at risk (Kunz et al. 2007). While other flying animals are also vulnerable, one study indicated that turbine-related bat fatalities exceed those of birds, and are a far greater concern (Grodsky et al. 2011).

Research on the implications of wind energy for bats has ranged from investigating factors attracting bats to turbines to tracking bat flight behavior using advanced technological methods. One such study combined acoustic tracking with Light Detection and Ranging (LiDAR) to study bat flight behavior in three-dimensional space (Hermans et al. 2023). The researchers used case studies on the behavior of bats around vegetation to present a proof-of-concept for combining those two methods. While the aforementioned study did not involve wind turbines specifically, similar methods can be used to track bat activity in wind research. At the Pacific Northwest National Laboratory, a thermal stereo vision technology called ThermalTracker-3D is used to track bird and bat flight activity at potential offshore wind farm locations (PNNL 2023). The system works by capturing three-dimensional flight tracks from thermal cameras in real time, which includes information that can determine the creatures’ size and infer their species. Similar studies have been conducted in other locations, including Iowa – one of the nation’s leaders in wind energy development. In the United States, Iowa has the second-highest installed wind energy capacity and the greatest wind energy development density (Mann et al. 2012). However, it is also home to migratory bat species, such as the federally-endangered Indiana bat (*Myotis sodalis*) and northern long-eared bat (*Myotis septentrionalis*), which are at risk of colliding with turbines during flight (Iowa State University 2024, Baerwald and Barclay 2009).

While research on the interactions of bats and wind turbines is growing, actionable results are limited by the technology available. Tracking bat activity around turbines is often approached using thermal cameras and software such as Yolo v3, a deep learning object detector (Adarsh et al. 2020). However, this process captures objects that aren't bats, such as flying insects, which can be difficult to distinguish by the human eye in low-resolution and long-distance thermal footage (Fang and Wu 2007). Currently, there is no system that can automatically and accurately classify flying objects as "bats" or "other". This poses an obstacle to effectively tracking bat activity, and can affect future measures to mitigate fatalities. One approach that shows potential for the automatic recognition and separation of flying objects is Support Vector Machine (SVM). SVM is a supervised learning algorithm that has previously been applied to human motion recognition, to classify motion in real-time and learn new types of motion for future recognition (Cao et al. 2009).

In this study, I ask how machine learning can be used to filter bat tracks from other flying objects in the footage from thermal cameras. Specifically, I ask how SVM can build a classifier that identifies data as either bat or unidentified flying object (UFO). I hypothesized that I could train SVM on numerical information extracted from the objects' reconstructed flight paths, to create a separating line between the two classes. I then ask what inputs would result in the most accurate classifier, which I predicted to be the number of points per track and distance between adjacent points in a track. Finally, I ask what mitigation strategies have shown the most success at reducing fatalities, and what factors attract bats to turbines in the first place.

METHODS

Study site

I studied a population of bats and UFOs detected by thermal cameras on a wind farm in central Iowa, USA. The wind farm is precisely located at latitude 41° 10' 56.3" and longitude -94° 8' 17.9", near the city of Macksburg in Madison County. It consists of 51 Siemens SWT-2.3 MW wind turbines, each with a rotor radius of 54 meters, hub height of 80 meters, and diameter of 108 meters, generating a total of 119.7 megawatts of energy. It is owned by MidAmerican Energy, a company based in Des Moines, Iowa that is the main power provider for a sizable portion of the American Midwest. I chose this study site due to its location, since Iowa has the greatest wind energy development density of all U.S. states, as well as several vulnerable bat species. Thus, my study site's high potential for fatal interactions between bats and wind turbines can have disastrous effects on an already dwindling population of bats. Additionally, bat fatalities could result in a loss of ecosystem services such as natural pest control, leading to economic losses in agriculture, and interfere with the wind farm's generation of power (Boyles et al. 2011).

Data collection

I obtained partial footage from one night with many flying object detections, recorded by a pair of thermal infrared cameras pointed at a tree at my study site, which researchers from the University of Iowa deployed to track bat activity. While UFO contamination occurs in thermal video of both wind turbines and trees, it is more prevalent around trees; therefore, I used footage of a tree that served as a control at my study site as a starting point for my analysis. I processed the footage using Dr. Aaron Corcoran's ThruTracker software (Corcoran et al. 2021), to reconstruct three-dimensional flight tracks of the path taken by the detected objects. From these tracks, I extracted points representing an object's position in (x,y) coordinates in each frame.

Classifying flying object tracks

To classify flying object tracks, I attempted to use SVM (Noble 2006), a supervised learning algorithm, to build a classifier that can separate tracks into two classes: bat or UFO. I manually assigned the labels "class 0" and "class 1" to a MATLAB dataset of tracks, based on each track's shape and location on the coordinate plane. I then extracted features of the objects' flight paths that I suspected to be distinct between classes, and plotted them on a coordinate plane with one point for each track. I attempted to find the line with the lowest margin of error to divide the plane into two domains – one for each class.

Selecting inputs to classifier

To select inputs to my classifier, I chose two features that I suspected were distinct between bats and UFOs: number of points per track and distance between adjacent points in a track. I expected the number of points per track to be greater for bats than UFOs, as insects – the primary UFO in my study – tend to spend less time in each frame of the footage than bats. For the same reason, I expected the distance between subsequent points to be smaller for bats than UFOs. From the objects' (x,y) positions in each frame, I calculated the number of points per track and distance between points for each track. I considered features that resulted in two or more distinct domains of tracks as valid inputs to my classifier, presuming that each domain contains tracks from one class of flying objects.

Mitigating future bat fatalities

To investigate the best approaches to mitigation, I reviewed literature on previous mitigation strategies and their success (or lack of success). Additionally, to explore potential causes of collisions between bats and turbines, I reviewed literature on factors attracting bats to turbines and affecting mortality rates. I collected this information in a data repository on Zotero (Zotero 2024), and analyzed how my classifier could inform previous mitigation measures and adapt them for greater efficiency at reducing the danger to bats.

RESULTS

Data collection

I found that I was able to extract twenty-nine flying object detections from my footage, and plotted their flight tracks. I then removed points that did not take the shape of tracks, which I assumed to be false detections, leaving twenty-one usable tracks each plotted in a unique color (Figure 1). I found that the majority of tracks were either (1) clustered in the upper left of the coordinate plane, in quadrant II, or (2) scattered below the line y=280, with a gap between the two sections. I found that tracks in the first category tend to take a straight diagonal shape, while those in the second category contain curves and a greater distance between subsequent points.

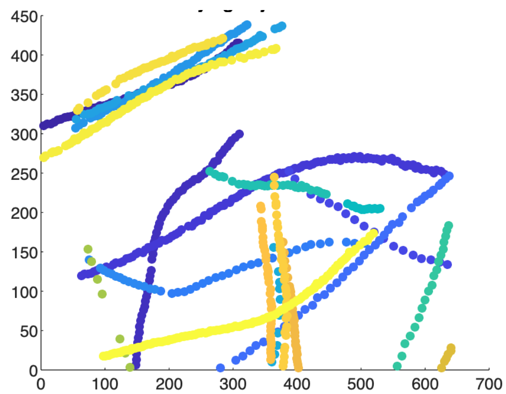

Figure 1. **Flying object tracks.** Twenty-one reconstructed tracks of flying object detections. An object's position in each frame is represented as an (x,y) coordinate pair. Each track is plotted in a different colour, and misdetections were removed.

Classifying flying object tracks

I found a distinct separation in the features of each class of flying objects (Figure 2). I found that tracks in class 0 generally had fewer points per track and greater distance between points than class 1, though there were a few outliers in class 0 with a high number of points per track. I was unable to find the line to separate the tracks into two domains, as I only considered a linear separator, and the optimal separating hyperplane would most likely be non-linear. However, the visible distinction between classes shows potential to find the separating hyperplane in the future.

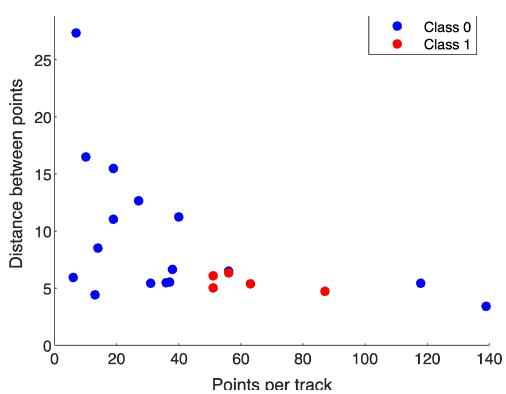

Figure 2. **Track features by class.** Points per track plotted against distance between points for flying object detections, with classes assigned at the track level and one point for each track. Visible distinction in values for tracks in either class.

Selecting inputs to classifier

I found the number of points per track to be an effective input to my classifier, as this feature resulted in two distinct classes of flying objects, marked by the gap between regions of points. Specifically, I found that tracks designated as class 1 tended to have 50 or more points, while those in class 0 (excluding outliers) had 40 or less. I also found that the distance between points in class 1 was concentrated around 5-10, while class 0 ranged from approximately 5-30. Hence, distance between points would not be an effective input on its own, but combined with the number of points per track, it provided useful information to classify flying object tracks.

Mitigating future bat fatalities

I found that the potential of wind energy to cause bat fatalities is elevated at lower wind speeds (Cryan et al. 2014). Consequently, reducing the motion of turbine blades in low wind speeds has shown significant success at mitigating fatalities; at a wind energy facility in Alberta, Canada, changing the minimum wind speed for turbine operation resulted in a 60% decrease in bat fatalities, while altering blade angles to reduce rotor speed resulted in a 57.5% decrease (Baerwald et al. 2010). Furthermore, I found that bats may actively forage for insects around wind turbines, leading to fatal collisions (Foo et al. 2017). I also found that bats tend to mistake turbines for trees, which increases the risk of collision. One study attributed 75% of bat fatalities in North America to tree bats, and suggested that migratory bats may be less likely to echolocate, which – along with increased flight activity during migration – puts them at greater risk of collision (Cryan and Barclay 2009). Moreover, I did not find evidence of selective turbine operation for conservation purposes, though one study shut down select turbines to improve power generation (Haces-Fernandez et al. 2019); such a method could be applied to deactivate turbine styles or layouts posing the greatest risk to bats.

DISCUSSION

Introduction

I found that there is potential for SVM to construct a hyperplane that separates the two classes of flying object tracks, which provides insight into the applications of machine learning in flying object identification. While the number of points per track was effective in distinguishing between classes, the values for distance between points were not as unique. I also determined that in mitigation efforts, shutting down turbines at low wind speeds has shown the most success, and may benefit from my findings. My classifier could be adapted to build a real-time detector that shuts down turbine operation when a bat is detected, and avoid shut-down when an object in the vicinity is not a bat.

Classifying flying object tracks

My results show that SVM may be an effective approach for sorting flying object tracks. While I did not find the separating hyperplane, SVM's success in similar studies suggests that future tracking efforts can use the algorithm to improve the accuracy of object classification. One such study applied SVM to the binary classification of gender in humans; the heights and weights of ten individuals were plotted on a two-dimensional coordinate plane, and the plane was divided into two regions – one female and one male – which could predict a new individual's gender from their height and weight (Stitson et al. 1996). I used a similar binary classification approach, with height and weight analogous to points per track and distance between points. While I did not consider a non-linear separating boundary, Stitson et al. discussed the potential for a non-linear separator, which could be further explored in the context of my study. Additionally, another study used SVM to distinguish raccoons from raccoon dogs, similar to how I attempted to distinguish bats from UFOs (Shalika et al. 2016). This shows the potential for using SVM to identify species, such as in my study. While Shalika et al. extracted features of the species from their camera capture images, I used features of the objects' tracks, since my footage is too low resolution and contains too few pixels for visual identification. However, Shalika et al.'s method may be applicable to future bat tracking efforts, if higher-quality cameras are used or the resolution of current footage is enhanced.

Selecting inputs to classifier

My results reveal that points per track is an effective classifying feature, resulting in a distinct domain of values for each class, while distance between points was more ambiguous. This suggests that future classification attempts can use points per track as a distinguishing feature, as long as it is paired with another feature that is distinct between classes. An effective feature is one that provides a high level of informativeness on object classes (i.e. feature importance), and therefore maximizes the percentage of correct class predictions assigned to new data by the classifier (Pisner and Schnyer 2020). Previous applications have used SVM to classify species of fish based on color features, statistical texture features, and wavelet-based texture features extracted from subimages of fish skin (Hu et al. 2012). While my study was limited to the relationship between two numeric features, Hu et al. used a set of multiple color and texture features, demonstrating the potential for a multi-feature SVM classifier. They also compare the outcomes of different types of SVM, such as directed acyclic graph multi-class SVM (DAGMSVM) and voting-based multi-class SVM (VBMSVM), which future attempts at flying object classification may consider.

Mitigating future bat fatalities

My findings show that efforts to mitigate bat fatalities would be most effective by raising the wind-speed trigger, i.e. the minimum wind speed for turbines to rotate, which is corroborated by my finding that turbine operation at low wind speeds poses an elevated risk to bats. According to one review, the creation of natural reserves carries potential for reducing fatalities, but has not been widely implemented (Peste et al. 2015). Similar to my approach, Peste et al. analyzed the success of previous mitigation measures to determine which are worth further pursuing. However, they reviewed mitigation attempts in Europe, so their results may not be relevant in the context of the United States, due to differing laws and practices around the management of wind energy facilities. Another study looked at the altitude, direction, and types of flight maneuvers for birds, bats, and insects (Horn et al. 2008). This research is one of few to consider both bats and insects in the context of wind energy, and similar to my study, used thermal infrared cameras to obtain data. Although Horn et al. focused on behavioral aspects, their analysis of the differences in bat and insect flight patterns provides a valuable basis for selecting features of tracks for classification. Furthermore, in assessing the impact on wind farms on birds, it was found that the rotor speed, size, and alignment of turbines affected the risk of collision (Drewitt and Langston 2006). While the researchers looked at birds rather than bats, their findings on collision risk could be extrapolated to bats as well, and incorporated in future mitigation attempts.

Limitations and future directions

I trained my classifier on data from a small study population, which may affect its ability to perform large-scale classification. Future studies seeking to utilize my approach should aim to use a training dataset of at least 100 tracks. Additionally, my study was limited to the linear separation of classes, though the optimal separating hyperplane may not be a straight line. Thus, there is high potential for future research to classify flying object tracks using a non-linear hyperplane. Moreover, while there was a notable distinction in points per track between classes, my classifier did not incorporate features other than points per track and distance between points, which future studies may consider when using SVM to classify flying object tracks. Although my footage is low-resolution and consists of too few pixels for deep learning, switching to high-quality research-grade cameras may make it possible to apply deep learning or other approaches, such as Convolutional Neural Networks, to flying object identification in the future.

Broader implications

My results show potential for further development of an SVM classifier to reduce or eliminate UFO contamination from bat tracks. Such a classifier could improve bat tracking around turbines, obtaining a more accurate estimate of the risk to bats; fatalities are currently underestimated, as bats struck by turbines often do not die on the wind farm, but travel a considerable distance before the impact of the strike fully affects them (Grodsky et al. 2011). Furthermore, an SVM classifier could be adapted into a detector to selectively control turbine operation based on the risk of mortality to bats, shutting down when a bat is detected but continuing operation in the presence of UFOs. In terms of management, the integration of biological and technological aspects is vital to the solution (Alvarez-Castañeda and Lidicker 2015). Above all, the gap in knowledge suggests that future research is an important step for the successful tracking and mitigation of bat fatalities at wind farms.

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