Insect Inspection on the basis of their Flight Sound

Glenes Concepta D'mello[1], Rashid Hussain[2]
[1]M.Tech Research Scholar,,[2]Associte professor.
glenesdmello@gmail.com, husaain1992@gmail.com.
Suresh Gyan Vihar University,Jaipur.

Abstract:-

This paper aims in monitoring the flying insects using their flight sound. Crop protection is one of the biggest issue in agriculture. In order to get high yield, we need to reduce the level of pest insect. The ability to use cheap, noninvasive sensors to correctly recognize flying insects cogent involvement in the area of entomology and aids in the evolution of many useful applications in vector control for both medical and agricultural entomology. However, none of the research had a lasting work. Here, we are presenting solutions of this problem by using several factors i.e. acousting sensing devices, a whack to read complex models with relatively little data. We are using pseudo-acoustic optical sensors which produces highly acute data. A different type of classification named Bayesian classification is used. This classification permit us to learn other 1models which are vigorous to overfitting. A general framework is introduced to inspect the insect adding additional feature.

Keywords: - Insect Flight found, Insect wingbeat, Bayesian Classifier, time of intercept, ex. Stigmatosoma, posterior probability, and neural network.

Introduction:-

The economy of India is the seventh-largest in the world by nominal GDP. One of the major sector of the dependency of India's economy is agriculture. Reduction of the level of pest insect leads to better yields of crops. A sudden change in climate and unexpected level of insects damages a large number of amount of plants. Generally, the monitoring of insects are done manually but it is not optimized. Therefore we proffer self -regulating system. We would like to have automatic classification so as to make cheap, universal and easy as present mechanical traps such as sticky traps or interception traps [1] along with features of digital device such as higher accuracy, very low cost, real-time monitoring ability and the ability to collect additional information. The basic problem arises for defining such classification are as follows:-

1) In some cases, insects are made to confine in a smaller places that had to be in the range of microphone [2-5]. However, it is hard to generalize the output for the insects in the natural conditions.
2) The difficulty of obtaining data implies that researchers have built classification models with very limited data [6]. However, it is said that for building classification models, more data are better [10-12].
3) The poor quality output and scattered data issue leads to use of very complicated classification models [6-8].

In this paper, we will mention that we have largely solved all these problems. We are using optical sensors to record the sound of insect flight from meters away that remain unaffected from meters away that remains unaffected from the wind noise and ambient sounds.

ISSN 2229-5518

We have acquainted a principled method to blend additional information into the classification model. The additional information can be taken on daily basis which are easy to obtain. Moreover, they produce rich gains in accuracy.

Background Study:-

In this paper, we are dealing with the inspection of mosquitoes. There are more than 3,500 species of mosquito wingbeat frequencies from 100 Hz to 1,000 Hz. If each species takes up a single wingbeat frequency then at least 2,600 species must share same wingbeat frequency with another species. Thus, a guaranteed condition of overlap rate will occur. This problem will increase if we consider more species. Grimaldi 1989 has mentioned this problem as the pigeonhole principle.

A Histogram created from measuring wingbeat frequencies of three species of insects, Culex stigmatosoma(female), Aedes aegypti(female), and culex tarsalis(male).

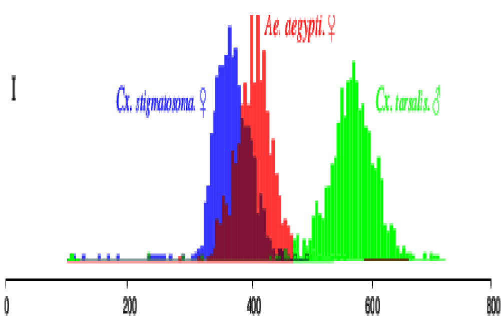


Figure 1

From the diagram it can be concluded that the wingbeat frequency of Cx. Stigmatosoma and Cx. Tarsalis are easily separable which can be used for accurate classification. However, we see that there is an overlapping between the wingbeat frequencies of Ae. Aegypti and Cx. Stigmatosoma. Hence it will be very difficult to isolate them. Therefore, we are winding up by using Insect flight sounds. It allows much higher classification rates than above because:-

1) Insect light sound contains more information than the wingbeat frequency.
2) Wingbeat sounds can be added for the better accuracy in classification.

We can augment another features like different flight activity circadian rhythms which deals with time of intercept information.

Flying Sound Recording:-

A very simple design is used to recognize the sounds of flying insects [13]. This arrangement abides a phototransistor array that is being joined up with an electronic board and a laser source evincing at the phototransistor array. An insect's wing will somewhat obstruct the laser light while flying transversely through it which causes some inconstancy in the light. These fluctuations are being arrested by the array which varies current. The signals are refined and augmented by the electronic board. The arrangement is shown in the figure below:-

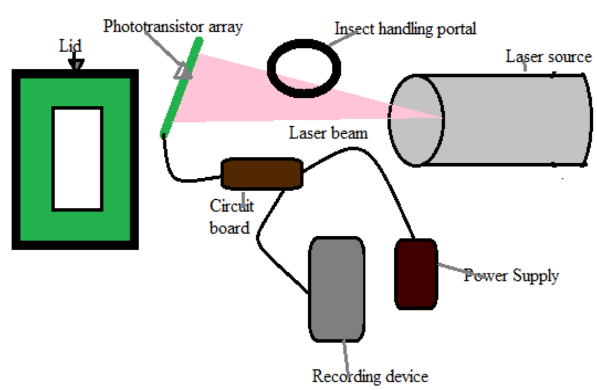


Figure 2

A digital sound recorder is feeded by the output of the electronic board which records the audio data in MP3 format.

Each MP3 file is of n hours long where n is a factor of 24. In this construction n is taken 6 hours long. A new file is recorded immediately after the recording

ISSN 2229-5518

for 6 hours making the receiving process continuous. The device firmware is used to limit the length of MP3 file.

Data Processing:-

This arrangement is extended where the MP3 sound files are downloaded to a PC. A suitable algorithm is used to excerpt the pithy insect flight sound from the unrefined data automatically. A classifier/detector is used to check whether the audio data segment consist the insect flying sound.

Here, the classifier used will be able to solve two simpler task. One is to differentiate between insect/non-insect. Another, to differentiate species and sex.

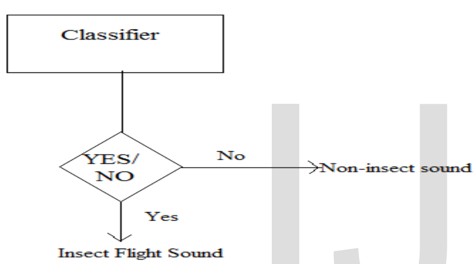


Figure 3

This classifier is based on the frequency spectrum and is a nearest neighbor classifier. Here is an example of one-second audio clip containing a flying insect generated by our sensor.

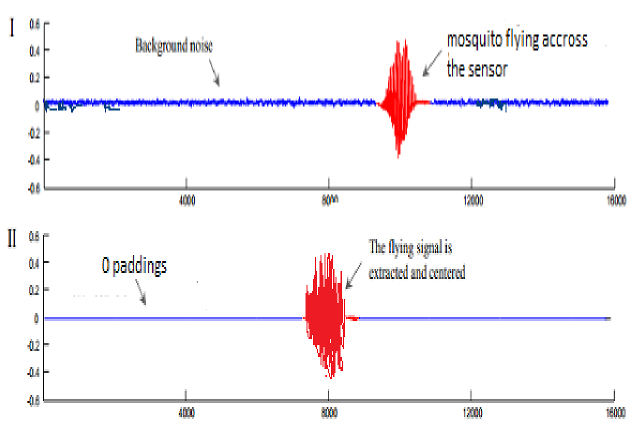


Figure 4

This audio is a high signal to noise ratio. It is clearly observed that the high fluctuation the non-insect sounds does not cause a serious problem. However, the amplitude of the insect sound is much higher and range of frequency is pretty different from that of the background sound thereby helping us to separate the insect sounds from the background sound.

Although a cleaner signal can be obtained if we apply the spectral subtraction [14] technique to every detected flying sound. This will reduce noise.

Advantages of Bayes Classifier:-

A simple nearest neighbor classifier is used to detect the flying sounds made by insects and process the snippets for further inspection. Bayes classifier works in very efficient way as it reduces the probability of misclassification. [15].Bayesian classifier has several advantages that makes it easily available for practice and specifically appropriate to the task at hand.

1. The Bayes classifier does not demand much from both CPU and memory requirements. The Bayesian classifier requires time and space resources that are just linear in the no. of features.
2. This classifier can be easily installed. It does not require tuning of many parameters like neural networks [7, 9].
3. This model is fast to build and demands only a small amount of data evaluate the parameters that has to be distributed in order to classify accurately.
4. This type of classifier can be easily handled by user. We can augment information extracted from other journal paper to the classifier.
5. The Bayesian classifier can frivolously handle the problem of missing values by simply ignoring the feature at classification time.

Neural network is the most frequently used classifier in the recent days [9]. However, Bayesian classifier comes out to be a far better output producer rather than the neural network.

The frequency spectrum of wingbeat snippets for three species are considered. Testing is done over 1,000 random resampling from the pool of training data of 1,500 objects. For the neural network, a single cloaked layer of size ten is used. The neural network classifier gradually follows the path of Bayesian classifier. However, it shows the worst performance for smaller data. On examining any dataset size [16], the neural network performs worse than the default rate of 33.3%.

Mathematical Expression:-

The mathematical expression for the Baye's classifier is given by the Bay's theorem. The expression is very easy to understand. In this, we have to find the most likely class observed from the given data. Let O be the observed data to a class A. The probability of an observed data O belongs to class A is given by (P/O) and is computed using Bayes rule:-

$$P\ (A|O) = \frac{P\ (A)\ P\ (O|A)}{P\ (O)}$$

Where P (A) is a prior probability of class A. P (O|A) is a probability of observing the data O in class A. P (O) is the probability of occurrence of the observed data O. The probability P (O) is usually unknown as it does not depend on the class. It is considered as a normalization factor. Therefore, only the numerator is considered for evaluation. Hence the probability P (A|O) is proportional to the numerator:-

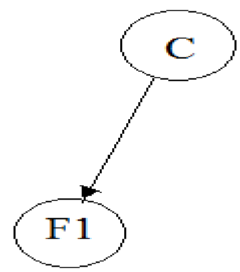
$$P\ (A|O) \propto P\ (A)\ P\ (O|A)$$

The P (A|O) is called the posterior probability. The highest posterior probability is assigned to the class A by the Bayesian classifier

A' = argmax P (A|O)

Where A is the set of classes, i.e. (A1= Ae. Aegypti, A= Cx. Stigmatosoma…….An=Ae. Gambie)

A graph named Bayesian network is used to represent a Bayesian classifier. A Bayesian network is represented using the diagram below. It has used a single feature for classification.



The direction of the arrow indicates that the probability of an insect to be a member of class A depends on the value of the feature F1 (wingbeat frequency). When the classifier is based on a single feature, the posterior probability that an observed data f1 belongs to class A is calculated as:

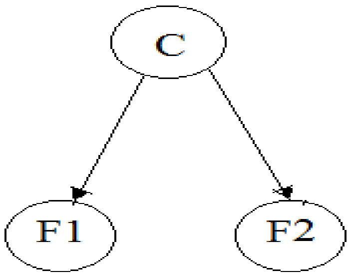
$$P\ (A|F1=f1) \propto P\ (A)\ P\ (F1=f1|A)$$

Where P (F1=f1|A) is class- conditioned probability of o observing feature f1 in class A.

Circadian rhythm of insect flying pattern:-

This can be combines as an additional feature to monitor the insects more accurately. This process is very simple as only time- of intercept has to be noted. However, this can lead to large improvement in classification. It has been studied that different kind of insects have different circadian flying pattern [20-21] and therefore when the flight sound is received, it is used to identify the insects. One of the benefit of using the Bayesian classifier that it offers multiple features to combine to it in a very simple way.

Here, the two features taken are insect-sound and time of intercept. These both features are conditionally independent. With such independency of feature assumption, the Bayesian classifier is called Naive Bayesian Classifier.



The presence of two arrows implies that the probability of an unknown data of a class depends on the features F1 and F2. However, the absence of arrow between F1 and F2 implies that both the features are independent. Now, an observed data should include two values f1 and f2. The posterior probability of O belongs to class A. The probability function is given as:-

$$P(A|F1=f1,F2=f2) \propto P(A)P(F1=f1|A)P(F2=f2|A)$$

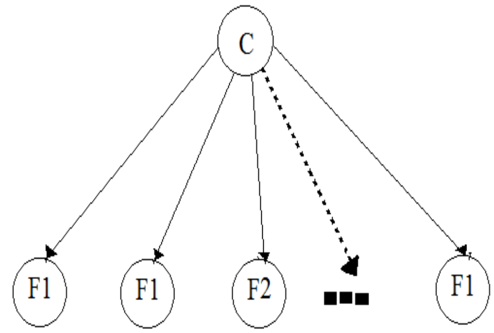
Where P ($F_j = f_j$|A) is the probability of observing the feature-value pair $F_j = f_j$ in class A.F1 is the insect sound and F2 is the time when the sound was produced.

General Framework:-

There are a lot of additional feature which could help in the betterment of classification performance. Some of the examples of such features are as follows:-

1) Height of intercept: - It's been known that some species of insects have a preferred height at which they fly [17].
2) Speed- of- intercept: - This feature may help to distinguish the insects on the basis of their speed.[18]
3) Location of intercept: - It is the location where the sensors has been installed. The sensors will estimate the relative amount of the species of insects at that location so that the monitoring can be done more accurately.

A generalize form of the classifier is shown through a framework. This framework is easily protractile to blend many such specialized features.



This is a Bayesian network which uses n independent features to classify insects. The posterior probability that an observation belongs to a class A is calculated as:-

$$P(A|F1=f1,F2=f2...Fn=fn) \propto P(A)\Pi P(Fj=fj|A)$$

Where P ($F_j = f_j$|A) is probability of observing f_j in class A.

Conclusion:-

In this paper, we have proffered a general framework for the classification of flying insects in a very cheap and easy way. These kind of system will surely help in agronomy by analyzing the environmental situations. The agro-ecological specialists will get a large amount of benefit by receiving the complete real-time and past factual environment information to achieve efficient management and utilization of agro-ecological resources. This paper has mentioned that the accuracy obtained from the system will be very helpful for the development of commercial products and can contribute a lot in entomological research. This framework is user-friendly as it is less complex and easy to understand.

Reference:-

1. Capinera, JL (2008). Encyclopedia of entomology. Springer. Epsky ND, Morrill WL, Mankin R (2005) Traps for capturing insects. In Encyclopedia of Entomology, pp. 2319-2329. Springer Netherlands.
2. Belton P, Costello RA (1979) Flight sounds of the females of some mosquitoes of Western Canada. Entomologia experimentalis et applicata, 26(1), 105-114.
3. Mankin RW, Machan R, Jones R (2006) Field testing of a prototype acoustic device for detection of Mediterranean fruit flies flying into a trap. Proc. 7th Int. Symp. Fruit Flies of Economic Importance, pp. 10-15
4. Raman DR, Gerhardt RR, Wilkerson JB (2007) Detecting insect flight sounds in the field: Implications for acoustical counting of mosquitoes.Transactions of the ASABE, 50(4), 1481.
5. Reed SC, Williams C M, Chadwick L E (1942) Frequency of wing-beat as a character for separating species races and geographic varieties of Drosophila. Genetics 27: 349-361.
6. Moore A (1991) Artificial neural network trained to identify mosquitoes in flight. Journal of insect behavior, 4(3), 391-396.
7. Li Z, Zhou Z, Shen Z, Yao Q (2009) Automated identification of mosquito (diptera: Culicidae) wingbeat waveform by artificial neural network. Artificial Intelligence Applications and Innovations, 187/2009: 483–489 .
8. Moore A, Miller JR, Tabashnik BE, Gage SH (1986) Automated identification of flying insects by analysis of wingbeat frequencies. Journal of Economic Entomology. 79: 1703-1706.
9. Moore A, Miller RH (2002) Automated identification of optically sensed aphid (Homoptera: Aphidae) wingbeat waveforms. Ann. Entomol. Soc. Am. 95: 1–8.
10. Halevy A, Norvig P, Pereira F (2009) The Unreasonable Effectiveness of Data, IEEE Intelligent Systems, v.24 n.2, p.8-12
11. Banko M, Brill E (2001) Mitigating the paucity-of-data problem: Exploring the effect of training corpus size on classifier performance for natural language processing. Proceedings of the first international conference on Human language technology research (pp. 1-5). Association for Computational Linguistics.
12. Shotton J, Sharp T, Kipman A, Fitzgibbon A, Finocchio M, Blake A, Cook M, Moore R (2013). Real-time human pose recognition in parts from single depth images. Communications of the ACM, 56(1), 116-124.
13. Batista GE, Keogh EJ, Mafra-Neto A, Rowton E (2011) SIGKDD demo: sensors and software to allow computational entomology, an emerging application of data mining. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 761-764.
14. Tsymbal A (2004) The problem of concept drift: definitions and related work. Computer Science Department, Trinity College Dublin.
15. Devroye L (1996) A probabilistic theory of pattern recognition. Springer Vol. 31.
16. Chen Y, Keogh E, Batista G (2012) UCR Insect Classification Contest, http://www.cs.ucr.edu/~eamonn/CE/contest.htm
17. Njie M, Dilger E, Lindsay SW, Kirby MJ (2009) Importance of eaves to house entry by anopheline, but not culicine, mosquitoes. J Med Entomol, 46:505–510.
18. Bidlingmayer WL, Day JF, Evans DG (1995) Effect of wind velocity on suction trap catches of some Florida mosquitoes. Journal of the American Mosquito Control Association, 11(3), 295-301.
19. Reisen, W (1993) The western encephalitis mosquito, Culex tarsalis. Wing Beats, Vol. 4(2):16.
20. Taylor B (1969) Geographical range and circadian rhythm. Nature, 222, 296-297 .
21. Taylor B, Jones MDR (1969) The circadian rhythm of flight activity in the mosquito Aedes aegypti (L.): the phase-setting effects of light-on and light-off. Journal of Experimental Biology 51, no. 1 (1969): 59-70.