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Estimation of population density of stored grain pests via bioacoustic detection

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ABSTRACT

The potential of bioacoustics in estimating the population density of insect pests inside the stored grain mass was evaluated in the laboratory. We used a piezoelectric sensor and a portable acoustic emission amplifier connected to a computer for recording acoustic emissions of insects. The software analyses the vibration recordings of the piezoelectric sensor, performs signal parameterization and eventually classification of the infestation severity inside the grain mass in four classes, namely: Class A (densities ≤1 adult/kgr), Class B (densities 1–2 adults/kgr), Class C (densities 2–10 adults/kgr) and Class D (densities >10 adults/kgr). Adults of the most important beetle pests of stored cereals and pulses, in various population densities (1, 2, 10, 20, 50, 100, 200 & 500 beetle adults/kgr grain) were used during the present study. The linear model was very effective in describing the relationship between population density and number of sounds. Multiple classifiers were used to evaluate the accuracy of bioacoustics on predicting the pest density given per minute counts of vibration pulses. Based on our results, our system's performance was very satisfactory in most cases (~68%) given that probabilities for successful prediction typically exceeding 70%. Our study suggests that automatic monitoring of infestations in bulk grain is feasible in small containers. This kind of service can assist with reliable decision making if it can be transferred to larger storage establishments (e.g. silos). Our results are discussed on the basis of enhancing the use of acoustic sensors as a decision support system in stored product IPM.

1. Introduction

More than 500 species of beetles have been reported to be associated with various stored grain products (cereals and pulses) and almost 100 of them may cause significant quantitative or qualitative losses. It has been estimated that between one quarter and one third of the world grain crop is lost each year during storage (Sarwar, 2015). The key for successful management of stored grain pests is not only early detection, but also an accurate population density estimation of the pest (Boxall, 1991; Rajendran, 1999, 2005, 2002).

Many methods have been developed today for the detection and monitoring of stored grain pests: visual inspection, trapping, sampling & sieving, heat-extraction, acoustic sensors and imaging techniques. High cost, limited capacity, intensive labour, time consuming, safety issues and low accuracy are the most important disadvantages that hinder the commercialization and large scale use of these methods by the grain industry (Fleurat-Lessard, 2011; Neethirajan et al., 2007; Rajendran, 2005). The most widely used and commercialized processes are sieving samples or the use of Berlese funnels (Neethirajan et al., 2007). Problems with these methods are that they are time consuming, have low accuracy and collect only 30–70% of insects in the grain samples (Minkevich et al., 2002).

Acoustic detection is a very promising method for early detection of insects inside the grain mass (Eliopoulos et al., 2015; Hagstrum et al., 1996; Mankin et al., 2011; Potamitis et al., 2009 and others). Insects of stored grain generate sound by eating, flying, egg laying, or locomotion. Reliability and efficacy of acoustic sensors has greatly increased in the last few years as a result of the development of improved acoustic devices and signal processing methods (Mankin et al., 2011). Apart from detection, very few studies have evaluated the potential of the acoustic method in estimating the population density of the pest inside the grain mass

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(Hagstrum et al., 1988, 1990).

Despite some increase in interest in recent years in bioacoustic signal processing of insect emissions (Mankin et al., 2008a), the combined applicability of signal processing and machine learning techniques to the problem of automatic insect detection and categorization is still in its infancy (Ganchev and Potamitis, 2007; Gaston and O'Neill, 2004; Mankin et al., 2008b; Potamitis et al., 2009). The efficacy of acoustic devices in detecting cryptic insects depends on many factors, including the sensor type and frequency range, the substrate structure, the interface between the sensor and the substrate, the temperature, the insect species and developmental stage, the assessment duration, the size and behavior of the insect, and the distance between the insects and the sensors (Mankin et al., 2011).

The aim of our study is to evaluate an automated monitoring procedure for IPM implementation in grain handling and storing facilities. The main unit is composed of a piezoelectric sensor and a portable acoustic emission amplifier connected to a computer. The software analyses the vibration recordings of the piezoelectric sensor, performs signal parameterization and eventually classification of the infestation severity of adult beetles inside the grain mass in four classes. Our results are discussed on the basis of enhancing the use of acoustic sensors as a decision support system in stored product IPM.

2. Materials and methods

2.1. Experimental insects

For the purposes of our study, we used adults from the most important beetle pests of stored cereals and pulses (Mason and McDonough, 2012; Rees, 2004) We used the grain that each species is most commonly associated with in natural conditions. Specifically, we recorded acoustic emissions of the rice weevil *Sitophilus oryzae* (L.) (Curculionidae), the lesser grain borer *Rhyzopertha dominica* (F.) (Bostrichidae), the confused flour beetle *Tribolium confusum* Jacquelin du Val (Tenebrionidae), the sawtoothed grain beetle *Oryzaephilus surinamensis* (L.) (Silvanidae), the rusty grain beetle *Cryptolestes ferrugineus* (Stephens) (Laemophloeidae), the cigarette beetle *Lasioderma serricorne* (Anobiidae) on wheat *Triticum* spp. L. and maize *Zea mays* L. (Poales: Poaceae), the larger grain borer *Prostephanus truncatus* (Horn) (Bostrichidae) on maize, the bean weevil *Acanthoscelides obtectus* (Say) (Bruchidae) on kidney beans *Phaseolus vulgaris* L. and butter (giant) beans *P. coccineus* L. (Fabales: Fabaceae) and the cowpea weevil *Callosobruchus maculatus* (F.) (Bruchidae) on broad (fava) beans *Vicia faba* L. (Fabales: Fabaceae).

All experimental species were kept in cultures in large glass jars (2 lt). Most species were reared on the grain where they were tested, except *O. surinamensis* and *C. ferrugineus* that were reared on a mixture of broken wheat: rolled oats: dried yeast (5:5:1), and *T. confusum* and *L. serricorne* that were reared on whole wheat flour (with 10% dried yeast) (Miller et al., 1969). All insect cultures were kept in environmental chambers under controlled conditions (25 °C, 60% R.H. and 16:8 L:D).

2.2. System description

Our system was adopted from Eliopoulos et al. (2015) and consisted of a 14 cm long piezoelectric sensor mounted on the end of a probe that was pushed into the grain (hard wheat) and a portable acoustic emission amplifier (AED-2010L, Acoustic Emission Consulting, Inc., Fair Oaks, CA) connected to a computer. The experimental procedure (grain preparation, recording methodology etc) is described in detail by Eliopoulos et al. (2015). Each of the 16 different treatments (recording of the desired species and number of adults in the desired grain mass) was replicated five times. Recordings from uninfested grain was used as a control.

2.3. Classification

Various infestation densities were tested during the present study (1, 2, 10, 20, 50, 100, 200 & 500 beetle adults/kgr grain). We proceeded by inserting the piezoelectric probe and taking 5 recordings per jar. We grouped insects' density in four distinct classes: Class A (densities $\leq$1 adult/kgr), Class B (densities 1–2 adults/kgr), Class C (densities 2–10 adults/kgr) and Class D (densities >10 adults/kgr). We applied supervised learning techniques to our dataset as we know the class labels (i.e. we set the infestation densities). During the operational phase, we first take a recording of the test jar and we subsequently derive the counts/min encountered in the recordings. Given the counts/min of the unknown test jar the classification algorithm predicts the Class (i.e. severity) of the infestation.

We had multiple choices on which specific learning algorithm we could use. This work did not aim to develop new classifiers nor did it aim to maximize classification through combinations of classifiers. It is interdisciplinary research exploiting the synergy of entomology, electronics and data analysis that results into an automated monitoring process. Therefore, we employed a variety of well-established classifiers that serve as standards in pattern recognition research: KNeighbors Classifier, Linear Support Vector Classification (SVC), Radial Basis Function (RBF) kernel SVM, a Decision tree (DecisionTreeClassifier), an aggregation of decision trees (RandomForestClassifier), AdaBoostClassifier meta-estimator, Gaussian Naive Bayes (GaussianNB) (Pedregosa et al., 2011). In operational mode, the computer receives a vibration recording from the sensor which turns into counts of enumerated pulses (counts/min). From these counts/min, it infers the distribution of probabilities over infestation severity classes A–D. By finding the maximum of the probability distribution (i.e. the most probable class) the algorithm can output a single decision. The classifier evaluation is based on prediction accuracy (the percentage of correct prediction of Classes A–D divided by the total number of predictions). In order to assess classifier's accuracy, we split the dataset into two mutually exclusive sets: (1) the training set to tune the classifier and (2) the validation set for estimating its performance. Our validation approach is called 'Leave-one-out validation scheme' and is a special case of cross validation partitioning. The training set is the whole dataset except one randomly selected case. The single hold-out instance is used to assess classifier's performance and the leave-one-out validation scheme is repeated for all instances of the dataset in-turn. The single hold-out instance is used to assess classifier's performance. This Leave-one-out iteration-validation scheme is repeated for all instances of the dataset in-turn. The average of the error rate of each test instance is therefore an estimate of the error rate of the classifier. We have chosen this validation, which is more expensive computationally, as the proper action to take when the dataset is small, as in our study.

All aforementioned classification algorithms can output a direct probability or a score that can be implicitly converted to a probability (e.g. in the case of Support vector machines-SVM) of each test instance belonging to each of the 4 classes. In Fig. 1 we show a case of expected output of a Random Forest directly classifying the counts of the vibration sensor. The procedure is as follows: a) Record for a sufficient period of time. The counts are turned to counts/minute regardless of the recording time. We used a minimum of 1 min of recording after 5 min of inserting the sensor in the bulk grain, b) input the recording to the counting algorithm (Eliopoulos