HARDWARE IMPLEMENTATION OF A SYSTEM CLASSIFYING THE OPTOACOUSTIC SIGNATURE OF INSECTS WING-FLAP

Ilyas Potamitis+, Konstantinos Fysarakis±, Didier Longueville‡ and Stavros Ntalampiras

+Technological Educational Institute of Crete, Dept. of Music Technology and Acoustics, e-mail: potamitis@staff.teicrete.gr

± Technical University of Crete, Dept. of Electrical and Computer Engineering, e-mail: kfysarakis@isc.tuc.gr

‡ HL2 group SAS, e-mail: didier.longueville@hl2.fr

In this paper we present a standalone hardware-implemented system that performs all signal processing stages necessary to classify the species of insects based on their wing-flap imprint as they fly. The recognizer classifies insect’s wing-beat recordings from an array of phototransistors receiving light from an infrared LED or laser. The wing-beat recording is based on the interruption of the emit-ted light due to the partial occlusion from insect's wings as they fly in typical traps. The classification module and the optoelectronic sensor are inserted in typical insect traps and perform detection, count-ing, recognition and transmission of results automatically. This work emphasizes the hardware im-plementation of the classifier performing all steps starting from the analog input to the final transmis-sion of results. We give all necessary implementation details needed to construct all circuit boards. We show recognition results for four insect species. We believe that once optimized the optoacoustic sensor and the standalone recognizer has the potential to revolutionize the way insect monitoring is carried out for a series of insects with large economic impact.

1. Introduction

Certain flying insect have a huge economic impact. Bees and silkworms have direct positive effects while many others shape our ecosystem by pollinating plants. Some flying insects produce extensive damage on stored products, crops and plantations by feeding on grain, leaves or fruits. Notable cases are the Olive fruit fly *Bactrocera oleae* (Gmelin) and the Mediterranean fruit fly, *Ceratitis capitata* (Wiedemann) some of the world's most destructive fruit pests, that in Europe alone cause billions of euros crop-loss/per year. Lastly, some flies and mosquito species transmit harmful viruses that cause serious illnesses, and even death, to humans, pets and livestock. In order to understand and assess the impact of insects one needs to have a picture of species existence, spatial distribution and density of population that can be provided by traps that are currently inspected by humans.

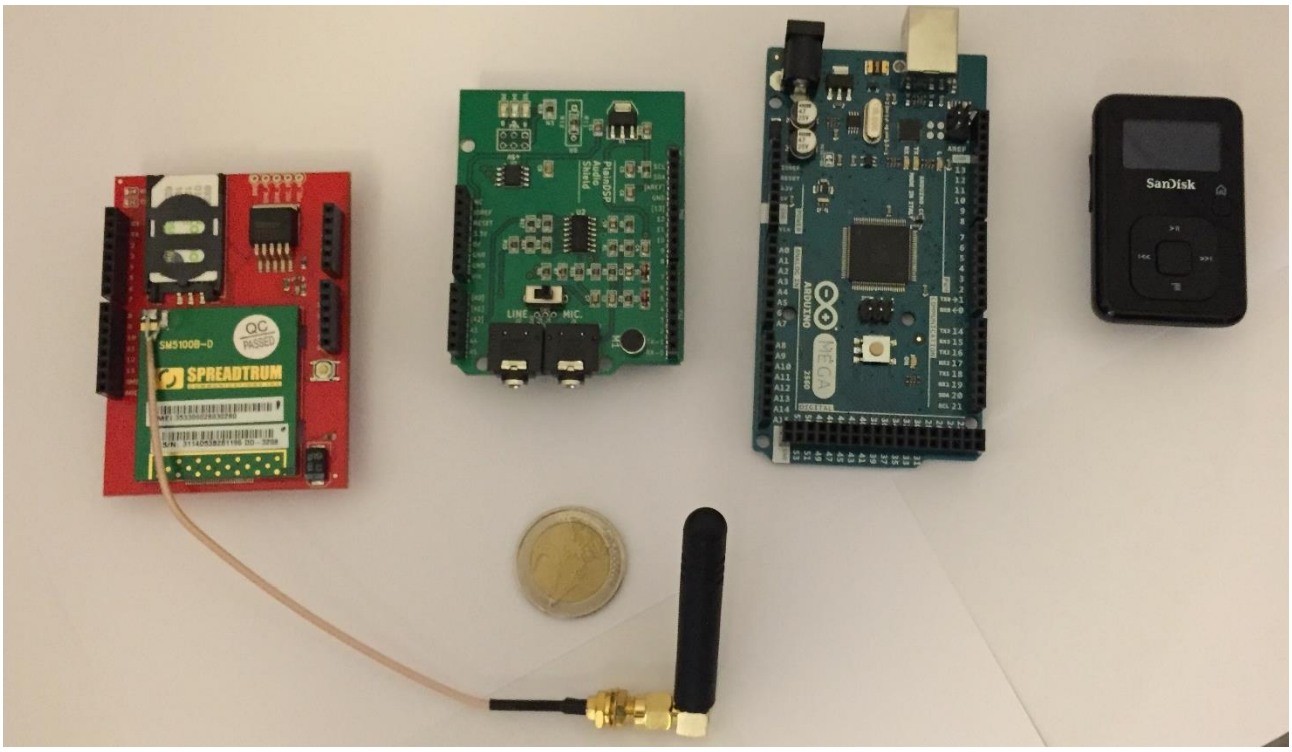
In this paper we put new work in context, by providing recognition results for our hardware implemented classifier. The targeted insects of economic and social importance are: *Ceratitis capitata, Culex quinquefasciatus male, Culex tarsalis female, Culex stigmatosoma female*. The system is able to detect all insect cases and additionally report the counts of the target species. We selected the fruit fly and *quinquefasciatus* (hereinafter referred as *quinx*) to be the target species.

In [1] we modified the typical plastic traps into electronic ones. Insects fly in the box-shaped traps that hang from trees in response to chemical signals they receive from inside the trap. As they fly-in, an optoelectronic sensor composed of an array of phototransistors that acts as a receiver and an infrared led on the opposite site of the circular entrance monitor the entrance. As the insect flies in its wings interrupt the flow of infrared light from emitter to receiver. The signal of the wing-flap received is of very high SNR and resolves the fundamental frequency of the wing-flap as well as several overtones up to 2 kHz. The analog signal of the wing-flap recording received from the optoelectronic sensors is directed to a microprocessor embedded in the trap that analyses the spectrum of the recording. The aim is to extract the fundamental frequency and the way the energy is distributed on the overtones of the recording. In [1] we have not shown detailed experimental results. Although he have developed a number of different sensor configurations, the efficiency of the electronic trap needs to be evaluated on a large number of insect recordings. Gathering a large number of recordings requires insectaries under controlled conditions of lighting, humidity and temperature. In this work we evaluated our hardware settings using a large available dataset of laser recordings of insects' wing-beat [2]. In [3-4] the authors have demonstrated that the short time signal of an insect passing by a sensors is enough to discriminate the species of the insect for a large number of recognition tasks. However, these results were achieved with powerful desktop computers and therefore were actually research oriented. This paper is product-oriented, therefore we need to balance between the competing needs of accuracy and other priorities such as the cost, real-time performance and power sufficiency. Algorithmic accuracy is highly ranked but it should be achieved with low-complexity algorithms that will allow real time performance and low power consumption. Construction cost is of importance but at present we focus on monitoring that requires a small number of traps and not on mass-trapping. The electronic trap, regardless if it is based on hi-tech facilities, cannot penetrate the market if it does not fulfil a real need: The important need is the reliable initiation of the spraying process at large scales and an estimation of where and how dense the problem is. The cost in crop loss due to an erroneous estimate of the initiation of the spraying process is very large compared to the cost of the electronic traps. We give details on the hardware implementation of the insect recognizer and its potential based on the integration of different Arduino shields and the embedded software. The novelties of this works are as follows: a) We integrate diverse hardware components in a functional whole, b) We test our hardware on real-data and we derive recognition scores on a medium size database, c) We test transmission of detections and recognition results through the General Packet Radio Service (GPRS) functionality and study the potential of such service, d) We give details of the embedded software and hardware sub-systems. The detection results of all entering insects are accumulated on per-day basis and an SMS with the results is emitted from the trap to base. Moreover the results are uploaded to a web server, to allow online monitoring. The SIM card and the GSM antenna are embedded in the microprocessor hardware. Therefore the recognition results and counts can be emitted as far as to another continent with minor cost.

We believe that once optimized the optoacoustic sensor and the standalone recognizer has the potential to revolutionize the way insect monitoring is carried out for a series of insects with large economic impact (either positive or negative) such as fruit flies, bees and mosquitoes.

2. Hardware Components

Figure 1. The microcontroller and its expansion boards: (from left to right). 1st) The GSM expansion board, 2nd) the audio expansion board, 3rd) MEGA microcontroller and 4th) the media player



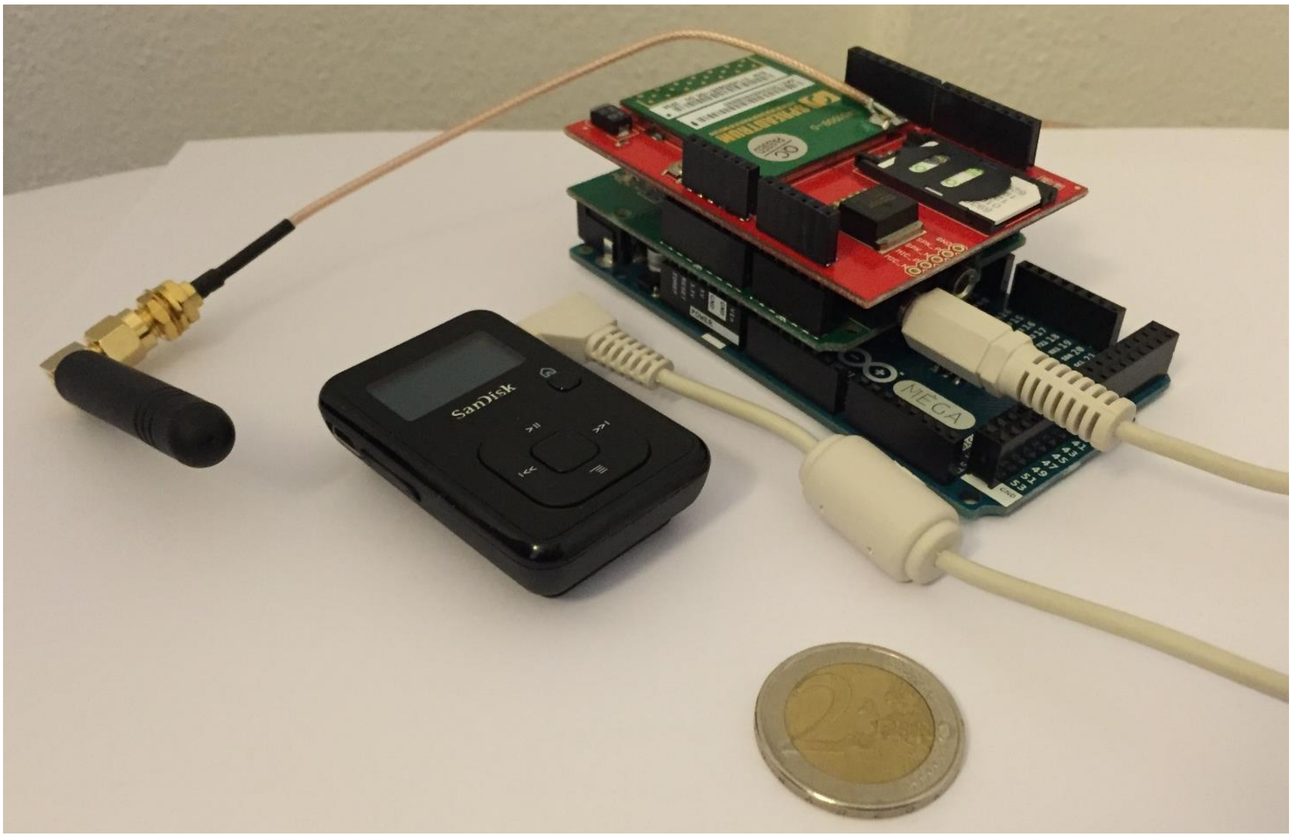


Figure 2. The microcontroller platform and its expansion boards assembled. All tests were inserted in the hardware through the media player (a two Euro coin as a comparison for size)

The basis of the hardware platform is an Arduino Mega2560 microcontroller (Atmel ATmega2560 microcontroller, 16MHz clock speed, 256KB Flash, 8KB SRAM, 4KB EEPROM). Moreover, this work makes extensive use of the PlainDSP library [5] that comes along with an Arduino expansion board (referred to as “shields”). As sound capture requires a wide range of power levels for detecting the weakest sounds (e.g. the fly of a mosquito) up to the loudest, the shield contains a self-adapting amplifier using three consecutive low noise operational amplifiers allowing an ultimate gain of x200, x2000 or x20000. The shield is fitted with an electret built in microphone for standalone applications and it features two jack ports for line input (e.g. computer, cell phone) and external microphone input. Three separate LEDs (Red, Green and Blue) allow visual outputs such as a simple VU meter (e.g. for power meter applications), bar graph (e.g. for frequency tuning applications) or light animations based on frequencies and tone. The kit comes with libraries which are compatible with most RGB led strips as used in many artistic creations. The PlainDSP library contains a set of functions required for running advanced Digital Signal Processing programs including the Fast Fourier Transform. The code has been written in such a clean and compact manner that this advanced function performs very well on the 8 bits, 16 MHz UNO and MEGA boards. It takes less than 100 ms to acquire a set of 128 samples and compute the corresponding frequency spectrum. Based on these performances, the PlainDSP opens the door to numerous applications, because of its low cost, reduced size and rather low power consumption. Designing high speed sound detection applications based on a combination of sound capture algorithms and spectral comparison algorithms. The development of such applications is made easy thanks to a transparent management of memory. PlainDSP works best when using up to half of the available memory from the micro-controller for the storage of input data and output results. The rest of the memory is still available for custom routines and functions. The FFT is executed in place, which means that only two vectors of data are required for input and output of both real and imaginary data and both fit into the reserved space. By default, all other DSP functions share the same source of data releasing a lot of the programming burden from the developer who can concentrate his efforts on signal processing and not on the management of memory, pointers and stacks. A direct effect of such construction results in fast development and high stability of firmware. As all functions contained in PlainDSP share the same data, it is very easy to build complex algorithms. Wing-flap detection and identification belongs to this class of advanced use of DSP. The fundamental idea behind the works done in the context of this application is a decomposition of the quantitative and qualitative analysis. While in idle mode, the Sound Pressure Level is computed out of a limited number of sound samples acquired at a fast rate. This routine iterates at a high speed so that bursts detection is always triggered in the same way: not in the middle of the burst, not sometime during the burst but always near the same trigger level. Then a full range sound spectrum is acquired and compared to one or more reference spectra previously acquired. The spectra comparison algorithm operate at acceptable speeds (actually few tens of milliseconds)

2.1 Uploading the detection results using GPRS

Other than the PlainDSP shield we have experimented with the applicability of a GPRS functionality. This can be exploited in various ways, in order to transmit results (e.g. counts of detected insects) or other data (e.g. battery status). For this application, the shield was used in two ways. The first and more complex approach uses GPRS data transmission to post each sensor platform’s data online (target counts, total counts, battery, GPS location etc.). More specifically, we used the dweet.io (https://dweet.io/) platform, a free web service that facilitates simple posting of data online from various internet-enabled devices. The data is then aggregated by another free service, namely Freeboard (https://freeboard.io), which allows visualization of the transmitted information. By combining the two platforms, we enable real-time monitoring of the status of the various platforms though a user-friendly online web interface, at no extra cost. The web interface we created for the purpose of this work is depicted in Figure 3.

A simpler transmission method was also implemented, which involved having the platform send a daily SMS message with target counts and total events to a predefined mobile phone number. This way, the owner of the assets (e.g. field) being monitored can get updates even when no internet access is available and/or when one is not computer inclined and thus not comfortable with using the web interface.

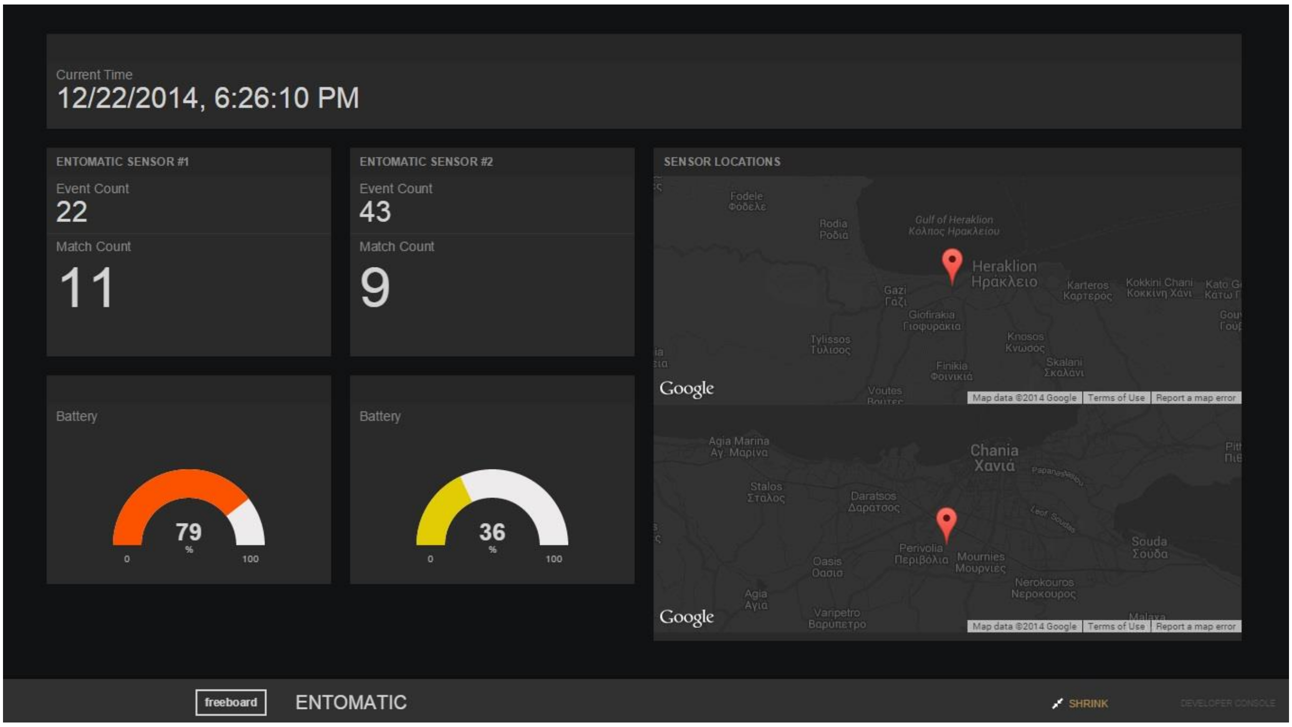


Figure 3. Detection and recognition results received from the GPRS module. The figure shows the online web interface that presents detection results of insects as well as detection results for the target species.

3. Signal processing

The analog output of the optoelectronic sensor wing-flap event is sent to the Arduino Mega2560 microcontroller platform that performs counting of insects passing the beam and recognition of the species.

The analog signal is captured and, depending on its level, amplified appropriately by an expansion board attached to the microcontroller platform. Capture signals are sampled at 4 kHz, digitized through the boards Analog-to-Digital Converter (ADC) and its root-mean-square values (RMS) are subsequently extracted. The sampling rate is enough to resolve the fundamental frequency of the wing-flap as well several overtones up to 2 kHz. A threshold level on the calculated RMS is set to trigger an event. Because of the high SNR output of the optoelectronic sensor the triggering is very reliable. The platform constantly captures the input from the sensor (storing the data in a circular buffer) but only processes the 512 samples when a triggering event occurs, to avoid overloading the microcontrollers processor and conserve resources (e.g. energy). The 512 samples at 4 kHz sampling rate correspond to a duration of 128 msec that is safely larger than the within-the-beam flight time of 50-100 msec observed from recordings processed offline. The count of trigger events is stored in the device’s memory and is transmitted at pre-set intervals (e.g. once a day) via text message to a predefined recipient. The latter is achieved via GSM expansion board which is also attached to the microcontroller. When no signal is present on the input, the board enters sleep mode to conserve resources.

The audio feature vector comprises a summarization of the useful information (from the perspective of pattern classification) hidden in the sound signal. The ability to carry out species-independent detection and recognition lies in the selection of distinguishing acoustic features that remain relatively invariant regardless of the way the insect entered the laser scanned area. In [4] a variety of temporal and spectral features are evaluated as to their usefulness for classification. We have observed two things with regards to the features:

1) Some features, though theoretically can be associated quite naturally with the identity of an insect species, are in practice error prone in their calculation due to the short-time of the useful signal (e.g. the fundamental frequency - *f0* or the harmonics and their associated amplitudes). Therefore, any parameter than needs to be estimated from an original raw measurement and will be subsequently fed to a pattern classifier will be error prone especially for species that have similar size and morphology but are actually different.

2) The main source of misclassifications results almost completely from species that are very similar in size and morphology (e.g. *Aedes aegypti* male can be misclassified to *Culex tarsalis* male but never as *Apis mellifera* -the common bee) which is a much larger insect compared to mosquitoes. In the evaluation of all approaches we employed a simple approach to extract the active region of the recording. We set a threshold for the RMS of the signal and once this is exceeded the 512 subsequent samples are sent for recognition (triggered event). The subsequent analysis is based on a single audio frame of N = 512 samples called s. We apply a normalisation that we found to work better that normalizing with the max value and this is:

$$s_i / \sqrt{\sum_{i=1}^{N} s_i^2}, i = 1,..,512 . \quad (1)$$

Normalisation is applied in order to match the spectrum of signals of the same species. We found that normalisation with the max value makes our system vulnerable to an outlier sample value. Then the data chunk is Fourier transformed and its magnitude is extracted.

The application allows the user to embed specific recordings as patterns. Using jumper wires on multiple pins of the microcontroller platform, it is possible to store an acquired reference spectrum in the EEPROM. Four reference patterns is the maximum that the microcontroller's EEPROM size of 4K allows, therefore grounding one of four different allows the acquisition of the corresponding pattern. As the EEPROM is non-volatile, the patterns can remain on the microcontroller indefinitely, even after a power failure event.

For our test we have embedded two characteristic recordings as patterns both from the target species. One should note that we use as reference the patterns of the target species and we monitor the distance between the unknown incoming signal and the stored patterns solely. Depending on the comparison of the difference with a threshold value derived from a validation subset a target event is called or not.

3.1 Distance measures

Although classification accuracy is the crucial factor, other factors such as simplicity of implementation and computational cost that is associated with power consumption are also of importance as the algorithms are meant to be embedded in stand-alone hardware devices. A highly accurate approach that would need a prohibitive amount of time and power in order to respond when embedded into hardware would be a poor choice against a suboptimal but simple and straightforward technique. In this work we examine the simplest possible approach and easier to embed. That is the square difference of the 256 amplitudes of the Discrete Fourier Transform (DFT) of the incoming signal Q and the stored patterns S_i , i=1,2.

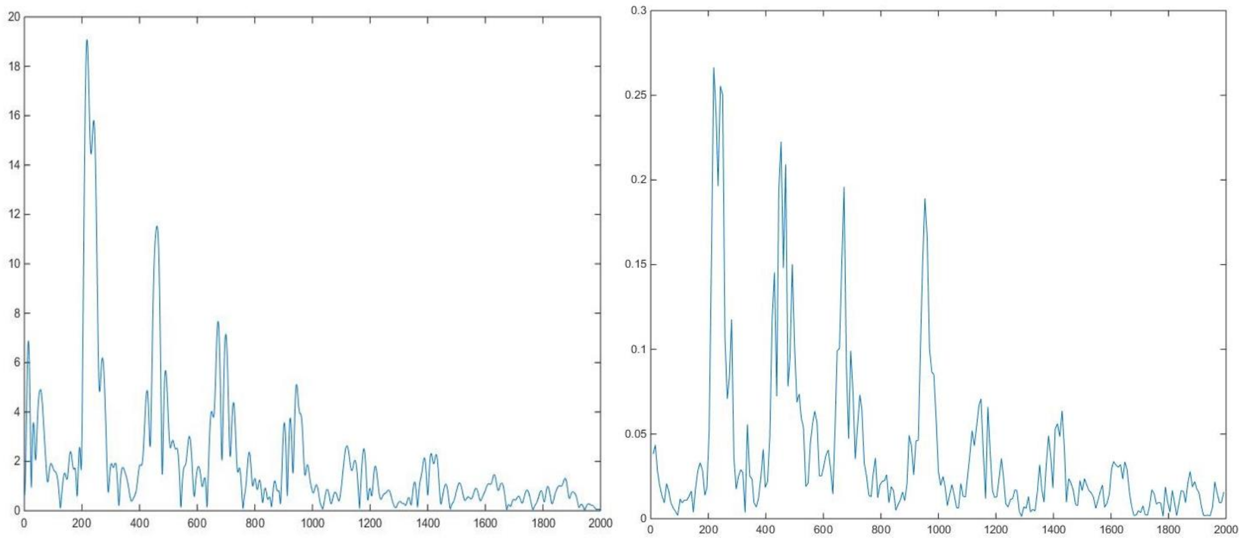


Figure 4. Spectrum of input waveform (left) and spectrum of waveform at microcontroller platform (right) after acquisition and processing. X-axis is the frequency axis in Hz.

(2) $$D(Q, S_i) = \|Q - S_i\|^2$$

The label of an unlabeled recording Q is assigned to the label of the S_i using a distance measure $D(Q, S_i)$ where i = 2 in our case.

Model-based approaches can achieve better results [2-4] but require a training phase so that they extract higher-level knowledge from labelled data, need a-priori the number of classes that they will classify, and are generally more complex than non-parametric ones. However, they are indisputably more accurate (with different levels of performance in each case). The a-priori knowledge of the number of classes in not a hard constraint for the type of application we aim for. That is the binary decision problem of the detection of a pest against all other classes that are not the target pest. Results achieved in section 3.2 prove the validity of our approach but also call for a step higher in recognition accuracy and thus in complexity.

4. Results

The work in [2] is associated with an open database of laser recordings of insects' wing-beat. We used a small subset of 100 files per insect category namely, *Fruit flies, Culex quinquefasciatus male, Culex tarsalis female, Culex stigmatosoma female,* totalling 400 files. We have used two recordings not included in the list of 400 recordings as representative patterns for each target species (fruit flies and *quinx*) respectively that are embedded in the trap. We compare each incoming signal to both patterns and if the distance is smaller than a threshold derived empirically on a validation set not included in the test set the unknown signal is classified as the target signal. We then repeat the same procedure for the *Quinx* male case (see Fig. 2).

The recordings are fed to the arduino shields using a portable media player. One should note that for 400 recordings the system detected 400 events. That is we did not miss an event and we did not count an event for two or call a silence part as an event.

Table 1. Detecting fruit-flies/Quinx against all other species respectively

Target	*Fruit flies*	*Quinx male*	*Tarsalis female*	*Stigma female*
Fruit flies	83/100	17/100	11/100	8/100
Quinx male	20/100	87/100	1/100	17/100

Table 2. Precision/recall/f-score for fruit-flies against all other species respectively

	precision	recall	f1-score	Support
Fruit flies	0.70	0.83	0.76	100
Not_target	0.94	0.88	0.91	300
Avg/total	0.88	0.87	0.87	400

Table 3. Precision/recall/f-score for Quinx against all other species respectively

	precision	recall	f1-score	Support
Quinx	0.70	0.87	0.77	100
Not_target	0.95	0.87	0.91	300
Avg/total	0.89	0.87	0.88	400

The results are preliminary but demonstrate that our approach is functional. More work needs to be done in order to increase the accuracy for real-field applications.

5. Conclusions

Detection and localization of insects in the field can become a valuable component of what is referred as precision agriculture as it will allow remote monitoring of targeted insects of economic importance. We constructed a hardware-based board that classifies insects' wing-beat and we report on embedding the classification software on the electronic circuit and transmitting counts and recognition scores. We integrated a microcontroller platform and tested the whole circle of events from detection to recognition and transmission of events to the pest manager using the GSM network. We anticipate that electronic traps can change the manual way insect monitoring is currently performed. The same technique under different configuration can be embedded in traps aiming at different insects such as mosquitoes (e.g. alerting for species that are possible carriers of the west Nile virus), bees and fruit flies. In the near future we will report results on separate cases.

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