A Novel Optical Sensor System for the Automatic Classification of Mosquitoes by Genus and Sex with High Levels of Accuracy.

María I. Gonzalez-Perez

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

Bastian Faulhaber

IRIDEON S.L

Mark Williams

IRIDEON S.L.

Josep Brosa

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

Carles Aranda

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

Nuria Pujol

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

Marta Verdún

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

Pancraç Villalonga

IRIDEON S.L.

Joao Encarnação

IRIDEON S.L.

Núria Busquets

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

Sandra Talavera (✉ sandra.talavera@irta.cat)

IRTA: Institut de Recerca i Tecnologia Agroalimentaries

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Abstract

Background

Every year, more than one billion people are infected and almost one million die due to vector borne diseases mainly transmitted by mosquitoes. Vector surveillance plays a major role in the control of these diseases that includes, as a key factor, a suitable and rapid taxonomical identification. New approaches for mosquito surveillance include the use of acoustic and optical sensors in combination with machine learning techniques, to provide an automatic classification of mosquitoes based on their flight characteristics, including wingbeat frequency. The development and application of these methods could enable the remote monitoring of mosquito populations in the field, which could lead to significant improvements in vector surveillance.

Methods

A novel optical sensor prototype coupled to a commercial mosquito trap was tested in laboratory conditions for the automatic classification of mosquitoes by genus and sex. Recordings of more than 4300 laboratory-reared mosquitoes of *Aedes* and *Culex* genera were made using the sensor. Five features were extracted from each recording in balanced datasets and used for the training and evaluation of five different machine learning algorithms to achieve the best model for mosquito classification.

Results

The best accuracy results achieved using machine learning were: 94.2% for genus classification; 99.4% for sex classification of *Aedes*; and 100% for sex classification of *Culex*. The best algorithms and features were; for genus classification: deep neural network with spectrogram; for sex classification of either genus: gradient boosting with Mel Frequency Cepstrum Coefficients among others.

Conclusions

To our knowledge, this is the first time a sensor coupled to a standard suction trap provides automatic classification of mosquito genus and sex with high accuracy using a large number of unique samples with class balance. This system represents an improvement of the state of the art in mosquito surveillance and encourages future use of the sensor for remote, real-time characterization of mosquito populations.

Background

Every year, more than one billion people are infected and almost one million die as a result of vector-borne diseases (VBDs). Approximately 80% of the world's human population lives with the risk of one or more VBDs [1]. In an increasingly connected world, travel and trade contribute to the spread of VBDs. Furthermore, a global warming scenario may lead to more favourable conditions for the survival and life cycle completion of the vectors [2] and may affect their abundance and distribution [3]. Mosquitoes (Diptera: Culicidae) and particularly those belonging to *Aedes*, *Anopheles* and *Culex* genera, are one of the deadliest vectors worldwide. Mosquito species can transmit diseases such as malaria, dengue, yellow fever, West Nile fever, Zika, Chikungunya and others [4]. According to World Health Organization directives [5] and European Centre for Disease Prevention and Control guidelines [6, 7] appropriate surveillance methods and indicators are needed to: determine the

composition and monitor changes in mosquito populations, identify the presence of new invasive species, monitor mosquito-borne diseases, quantify the transmission potential of vectors and enable the design of accurate control programs.

A range of insect trap types and methods are used in regular monitoring and surveillance of immature and/or adult mosquito populations [8]. Although immature stage monitoring can be easier to set up, it is not useful for estimating adult abundance due to the lack of correlation between egg, larval and pupal density indices, and adult indices [9]. Studies show that the seasonal variation in mosquito abundance is better represented by adult trap monitoring than by other indices (e.g. House Index) based on immature stages [10]. Therefore, adult mosquito surveillance is generally the most widely applicable and accurate solution, especially for VBD risk assessment [11]. Many adult mosquito monitoring systems rely on traps using light, chemical attractants or CO₂ as a bait. Most traps include a suction fan to draw approaching insects into a catch bag within the trap, and such types have been successfully used in a great number of studies [12–14]. However, they require the catch bag to be periodically collected in the field, followed by a time-consuming process of identification of the collected specimens by entomologists. The time delay between insect trapping and analysis may limit the correct characterization of the temporal dynamics of mosquito populations. Such delays may also result in degradation of the insects in the catch bag because of desiccation or predation. New approaches for entomological surveillance include novel optical sensors to sense the characteristics of flying mosquitoes and analysis methods including machine learning methods to enable classification of mosquitoes in near real-time [15–19], which is crucial for surveillance programs.

Since the 1940s, microphones have been used to sense the audible flight tones emitted by flying mosquitoes which may be associated with a particular mosquito genus, species, or sex [20]. Acoustic methods are still employed today in applications such as sound traps which emit species and sex specific sound frequencies to attract mosquitoes [21] and in classification systems such as those in which citizen scientists use their mobile phones to record mosquitoes [22, 23]. However, it is hard to obtain acceptable quality audio recordings of free flying insects in the field due to the presence of background noise [18]. To address this, optical methods have been employed, in which a light source is used to illuminate the flying insect and a light sensor is used to detect the light reflected and scattered, or attenuated, by the insect in flight [24–30]. The use of optical methods in this field began in 1955 when a photoelectric cell was used to detect the light modulation produced by a flying insect crossing its field of view [31]. In recent years, several optoelectronic sensors have been developed and used in conjunction with machine learning techniques to classify flying mosquitoes, with promising levels of accuracy [16, 17, 32–34]

Variables known to condition mosquito wingbeat fundamental frequency include taxonomy, sex, parity status, size, and environmental temperature [35–38]. Historically, wingbeat frequency has been used as the only predictor variable for mosquito classification, but it appears insufficient on its own to differentiate between mosquito species, especially those of the same genus [18]. This could limit field applications, where different mosquito species can coexist, with the possibility of overlap in wingbeat frequency distributions [39]. Efforts have been made in recent years to improve classification methods to distinguish between mosquito species, sex and even parity status [16, 17, 35]. In some cases, more advanced optical approaches have been used, for example to determine insect body and wing depolarization ratio, to improve the accuracy of classification [17].

In addition to the selection of the proper predictor variables and machine learning algorithms, the use of metadata such as the climatic conditions, the spatiotemporal localization and other ecological features accompanying mosquito captures may also be relevant for remote mosquito classification in the field [18, 33], since different mosquito species have different behaviour and ecological needs (geographical distribution, climatic range, circadian rhythm, peaks of activity, etc.). According to new paradigms of remote mosquito surveillance, wingbeat sensor information and metadata could be sent wirelessly in real-time to a server using *Internet of Things* (IoT) technology [40–42] with the potential to improve entomological surveillance.

Currently there is only one commercial optical sensor product available for the remote monitoring of mosquito populations [40]. It is called the BG-Counter (Biogents, Germany), which according to the company, can distinguish mosquitoes from other insects and count mosquitoes. However, the sensor does not provide information about mosquito genus, species, sex or other attributes.

In this study, we present the results of a prototype optical sensor, which is coupled to the entrance of a commercial mosquito trap. The trap is of a type widely used for mosquito surveillance in the field and contains a suction fan. The fan causes the mosquitoes to pass through the sensor more quickly and with a more perturbed wingbeat compared to free flight conditions as described in another work [43]. For the present work, 4335 flights from mosquitoes of *Aedes* and *Culex* genus were recorded using the sensor. A set of features were extracted from each recording and used to train a series of machine learning algorithms to determine which combination of feature and algorithm gave the best performance in classifying mosquitoes by genus and sex.

Methods

Mosquito rearing conditions

Three species of mosquitoes, from two genera, were used to generate the dataset:

i. *Culex pipiens*, population of Gavà (2012), Barcelona, Spain
(41.3000°, 2.0167°)

ii. *Aedes albopictus*, population of Sant Cugat del Vallès (2005), Barcelona, Spain
(41.4667°, 2.0833°)

iii. *Aedes aegypti*, population of Paea (1994), Tahiti, French Polynesia
(-17.6889°, -149.5869°)

The mosquito populations were all reared under controlled environmental conditions in a climatic chamber at a temperature of 28 °C and a relative humidity of 80%, with a light:dark photoperiod of 12:12 hours, except for *Cx. pipiens* (with a light:dark photoperiod of 11:11 hours plus 1h of dusk and 1h of dawn). *Culex pipiens* and *Ae. albopictus* were reared in biosafety level 2 (BSL2) laboratory and *Ae. aegypti* in a biosafety level 3 (BSL3) laboratory at IRTA-CReSA facilities. Larvae were maintained in plastic trays with 750 ml of dechlorinated tap

water (renewed three times per week) and were fed with fish pellets (Goldfish Sticks-TETRA, Melle, Germany) *ad libitum*. Pupae, upon appearance, were immediately placed in insect cages (BugDorm-1 Insect Rearing Cage W30 x D30 x H30 cm, MegaView Science, Talchung, Taiwan). After metamorphosis, adults were fed with sucrose solution (10%) *ad libitum*. Females were not fed with blood to avoid any body-size or flight variation. For *Aedes* females, the sucrose solution was removed 24 hours before the sensor tests. For *Cx. pipiens* females, this was done 48 hours before, to improve their affinity for the attractant used in the trap.

Sensor and trap description

The prototype sensor was designed and produced by Irideon S.L. (Barcelona, Spain) and was coupled to the entrance of a commercial BG-Mosquitaire suction trap from Biogents AG (Regensburg, Germany), as shown in Fig. 1a.

The trap coupled to the sensor was placed in an insect rearing cage (BugDorm-4S4590 W47.5 x D47.5 x H93.0 cm, MegaView Science, Talchung, Taiwan). The trap was fitted with a sachet of BG-Sweetscent chemical attractant from Biogents AG. The air flow generated by the fan was approximately three metres per second in the downward direction. When a mosquito flies close to the entrance funnel of the sensor, it is sucked in by the fan, detected by the sensor and trapped in the catch bag inside the body of the trap.

The sensor contains an optical emitter panel and an optical receiver panel which face each other through a transparent flight tube with a diameter of 105 mm. The optical emitter comprises a two-dimensional (2D) array of 940 nm wavelength infrared light emitting diodes (LEDs); and the optical receiver comprises a 2D array of 940 nm photodiodes. The optical sensor has an active length of 70 mm in the downward direction. The basic operating principle of the optical sensor is illustrated in Fig. 1b.

The output of the optical sensor is amplified and acquired by an analog to digital converter (ADC) with a sampling frequency of 9603 samples per second. When a mosquito enters the sensing volume, it automatically triggers a recording of up to 1024 samples, i.e., of up to 107 milliseconds duration. The duration of a typical mosquito flight is around 50 milliseconds. The sensor automatically adds a timestamp to each recording, along with the measured ambient temperature.

Data acquisition process

Mosquitoes from *Aedes* and *Culex* genera were anesthetized with carbon dioxide 48 and 72 hours respectively before each experiment. They were separated into groups by species (*Cx. pipiens*, *Ae. albopictus* and *Ae. aegypti*) and sex (male, female).

Culex pipiens and *Ae. albopictus* were introduced into the insect rearing cage in batches of 20 individuals to reduce the chance of multiple mosquitoes passing through the sensor simultaneously. Batches of 10 individuals were used for *Ae. aegypti*, due to their greater affinity to the attractant. All mosquitoes were introduced at some distance from the trap to ensure that they could fly freely until they approached the trap, to best approximate field conditions.

Each recording corresponds to a different mosquito, i.e., trapped mosquitoes were not re-used to generate more recordings. Wingbeat files were tagged with species and sex class by the operator. After each experiment, the wingbeat recordings were downloaded from the sensor and processed using a Python script to produce playable and viewable audio files, as depicted in Fig. 1c. Wingbeat recordings were examined manually, and those deemed to be invalid, such as recordings containing more than one mosquito, were excluded from the dataset.

The resulting dataset contained 4335 wingbeat recordings, comprising: 2472 of *Aedes* genus (882 *Ae. aegypti* and 1590 *Ae. albopictus*) and 1863 of *Culex* genus (all *Cx. pipiens*). There were 1211 *Aedes* females, 1261 *Aedes* males, 964 *Culex* females and 899 *Culex* males. The average ambient temperature measured for each of the classes was in the range of $25.8 \pm 0.1^\circ\text{C}$.

Feature extraction

The following five features were extracted from each wingbeat recording via the application of digital signal processing methods:

- The power spectral density (PSD) shows the power of the signal at different frequencies. It is calculated using Welch's method [44], in which the wingbeat recording is divided into several overlapping segments. A windowing function is applied to each of the segments and a series of periodograms is obtained by calculating the power spectrum of each windowed segment. Finally, the periodograms are averaged to give the PSD [45]. A PSD plot of a typical mosquito recording is shown in Fig. 2a.
- Wingbeat fundamental frequency in Hertz [Hz] is determined from the PSD using a peak search method. The wingbeat fundamental frequency is the frequency at which a mosquito flaps its wings. It is characteristic of mosquito taxonomy and sex, and varies depending on intrinsic variables of mosquito biology (size, age, parity status, mating behaviour) [16, 35, 36, 38] and environmental variables such as temperature [37]. The typical range of mosquito wingbeat fundamental frequencies is 300 to 900 Hz [39].
- The fundamental peak power density [dB/Hz] (hereafter referred to as fundamental peak power) is also determined from the PSD (see Fig. 2a) and represents the peak power density of the sensor output at the wingbeat fundamental frequency. It is equivalent to the intensity of the sound produced by a flying mosquito, typically ranging from 40-80 dB [46, 47].
- The spectrogram is a series of spectra calculated from multiple overlapping segments of the wingbeat recording. Each spectrum is generated by applying a Fourier transform to the segment to provide information about the amplitude of the various frequency components in the segment. The spectrogram represents the variations of the frequency content of the signal over time, rather than an average for the whole signal as given by the PSD [48].
- Mel Frequency Cepstral Coefficients (MFCCs) are calculated by converting the frequencies of a spectrogram to the Mel scale and applying overlapping triangular filter banks before calculating the cepstrum, by transforming the spectra to a logarithmic scale, and then applying an inverse Fourier transform [49]. Please refer to Additional file 1 and Fig. 4 for further details.

Each individual feature and one combined feature (fundamental frequency and fundamental peak power) were used for the machine learning models.

The wingbeat fundamental frequency and peak power features for the entire dataset are shown in the scatterplot of Fig. 2b. The remaining features cannot be visualised directly in this manner because each of those features contains multiple values. Two clusters are seen within each genus, in which the left cluster (below 580 Hz approximately) corresponds to females of the species, and the right cluster to the males.

Machine learning

The goal of the machine learning process was to compare the performance of five selected machine learning algorithms using the features described above, in classifying mosquito genus and sex. A labelled dataset consisting of the feature set was used to train, evaluate, and compare the classification models. The following five machine learning algorithms were used: logistic regression (LR), gradient boosting (GB), random forests (RF), support vector machines (SVM), and a fully connected deep neural network (DNN). These algorithms were chosen due to their widespread usage and good performance [50]. A brief description of each algorithm is given below.

- LR was proposed in the late 1960s as an alternative to ordinary least squares (OLS) and linear discriminant analysis (LDA). It fits a sigmoid function to the observations (predictor variables and labels) to generate a classification model [51].
- GB was first described in 2001 [52]. It uses the decision trees ensemble model which consists of different classification and regression trees (CART). In GB, the ensemble building is done incrementally so that each new tree helps correct the error of the previous tree [53]. The optimized *XGBoost* library was used [54].
- RF also uses the decision tree ensemble method, but it grows the different trees simultaneously from a randomly chosen subset of the predictor variables and then they vote on the outcome [55].
- SVM dates from the late 1970s. This algorithm constructs decision boundaries between different classes and optimizes the margin between them [56].
- DNNs mimic the structure of the human brain and consist of multiple layers of relatively simple processing units that receive input and give output. The use of multiple layers allows for non-linearity between predictor variables and outputs [57]. DNNs originated in the 1960s but have only recently gained traction and have won numerous pattern recognition competitions [50].

The decision tree representing the logic of the classification process is shown in Fig. 3. Three classification tasks were performed: one genus classification (*Aedes/Culex*) and two sex classifications (male/female), one for each genus (sex of *Aedes*, sex of *Culex*).

Balanced datasets, i.e., datasets that contained an equal number of samples in each class were used to make an unbiased assessment. They were obtained by randomly under-sampling the classes which had a higher number of available samples. Of each dataset, 75% was used to train each model, and the remaining 25% was used to test it. The training and test sets were generated by randomly sampling from the balanced dataset. The

test set contains samples upon which no prior training or evaluation has been done, to assess how well the trained model generalizes on new data.

The machine learning algorithms use configuration parameters, called hyperparameters, which can have a significant impact on performance. Here, the hyperparameters were optimized using 4-fold cross-validation, meaning that in each training, a portion of the training set was set apart to evaluate the model. In 4-fold cross-validation, the training set is split into four parts of equal size and the model being optimized is trained on three of the four parts and evaluated (cross-validated) on the fourth part. This process is done four times using a different part of the training set for the cross-validation in each iteration. The final cross-validation score is obtained by averaging the four evaluation results. The hyperparameter configuration with the best cross-validation score is selected as the best model and then evaluated on the test set.

As evaluation metric to compare models, accuracy was used. It is given by dividing the number of correct predictions of the model, by the number of total predictions. While being a simple evaluation metric, thus making it easy to interpret, it is also adequate when using balanced datasets.

Training and validation accuracies were also used for model evaluation and error analysis. If the training accuracy is considerably higher than the validation accuracy, then this indicates overfitting, so more data samples could help improving the model. If, on the other hand, training and validation accuracies have a similar low score, the model is too simple and obtaining more training data would not help. An algorithm which is able to learn more complex relationships or more features could improve the model in this case.

Results

Genus classification

In the genus classification, mosquitoes were classified into *Aedes* and *Culex* genus. A total of 2688 samples were used for training and testing: 1344 samples of *Aedes* (including 672 *Ae. albopictus* and 672 *Ae. aegypti*) and 1344 samples of *Culex* (all *Cx. pipiens*). An equal number of males and females was used. The training set had 2016 samples (75% of the total) and the test set had 672 samples (25% of the total). The accuracy results for genus classification are shown in Table 1 with the best performing algorithm for each feature shown in bold. The best result for genus classification was obtained for the DNN algorithm trained on the spectrogram feature, with an accuracy of 94.2%.

Table 1
Genus classification accuracy results, with best results per feature in bold.

Algorithm					
Feature	Logistic regression	Gradient boosting	Random Forest	SVM	DNN
Fundamental frequency	55.2%	67.3%	65.9%	65.5%	66.1%
Fundamental peak power	68.9%	70.1%	69.6%	69.8%	70.0%
Fundamental freq. & peak power	70.1%	77.7%	77.2%	77.2%	77.8%
PSD	84.8%	92.3%	89.0%	90.5%	90.3%
Spectrogram	90.5%	93.2%	91.2%	93.4%	94.2%
MFCC	89.3%	93.2%	90.2%	93.0%	93.2%

Sex classification of Aedes

In this classification, mosquitoes of the *Aedes* genus were classified into males and females. For training and testing, 1344 samples were used, comprising 672 females and 672 males, with each sex group comprising 336 *Ae. aegypti* and 336 *Ae. albopictus*. The results for this classification are shown in Table 2. The best performing algorithms for sex classification of *Aedes* were logistic regression trained on spectrogram and MFCC, and gradient boosting trained on MFCC, with an accuracy of 99.4% in each case.

Table 2
Results of sex classification for Aedes, with best results per feature in bold.

Algorithm					
Feature	Logistic regression	Gradient boosting	Random Forest	SVM	DNN
Fundamental frequency	95.5%	95.5%	95.5%	95.5%	95.5%
Fundamental peak power	86.9%	89.5%	89.5%	89.2%	89.3%
Fundamental freq. & peak power	98.2%	96.7%	97.0%	98.5%	97.9%
PSD	97.0%	98.8%	97.9%	98.8%	98.2%
Spectrogram	99.4%	98.8%	98.8%	99.1%	98.8%
MFCC	99.4%	99.4%	98.8%	98.8%	98.8%

Sex classification of Culex

In this classification, mosquitoes of the *Culex* genus (all *Cx. pipiens*) were separated into males and females. For training and testing, 1560 samples were used, comprising 780 females and 780 males. The results for this classification are shown in Table 3. For *Culex* sex classification, a perfect accuracy of 100% was achieved by all

five algorithms trained on MFCC; and by logistic regression, SVM and DNN trained on spectrogram; and by SVM trained on PSD.

Table 3
Results of sex classification for *Culex*, with best results per feature in bold.

Algorithm					
Feature	Logistic regression	Gradient boosting	Random Forest	SVM	DNN
Fundamental frequency	98.0%	98.0%	98.0%	98.0%	98.0%
Fundamental peak power	83.4%	81.3%	81.5%	83.1%	83.6%
Fundamental freq. & peak power	98.7%	98.7%	98.5%	98.7%	98.7%
PSD	99.7%	99.2%	99.2%	100%	99.7%
Spectrogram	100%	99.7%	99.7%	100%	100%
MFCC	100%	100%	100%	100%	100%

Summary of the best model performance results

A summary of the best performing algorithms and features for each classification is given in Table 4 in which training and cross-validation accuracies were used for error analysis, to indicate how the results might be improved.

The best accuracy results were 94.2% for genus classification, 99.4% for sex classification of *Aedes* and 100% for sex classification of *Culex*.

For genus, the training accuracy was 100% and the cross-validation accuracy was significantly lower (95%), which indicates that the model overfits slightly and its performance could possibly be improved with more training samples.

For *Aedes* sex classification, although the best models gave a near perfect accuracy, the training accuracy and cross-validation accuracy are similar (99.5%), which indicates that the model could possibly be improved with a more complex algorithms and/or features, rather than with more training samples. In case of *Culex* sex classification the accuracy was 100%, so no error analysis was necessary.

Table 4
Summary of machine learning classification results.

Classification task	Best accuracy	Best feature	Best algorithm	No. of samples	Training accuracy	Cross-validation accuracy	Error analysis indication
Genus	94.2%	Spectrogram	DNN	2688	100%	95%	more training samples
Sex <i>Aedes</i>	99.4%	Spectrogram	LR	1344	99.5%	99.5%	more complex
		MFCC	LR, GB				features or algorithm
Sex <i>Culex</i>	100%	PSD	SVM	1560	100%	100%	No error.
		Spectrogram	LR, SVM, DNN				
		MFCC	All algorithms				

Discussion

In the present study, 4335 mosquito flights were recorded using a novel optical sensor. The sensor was attached to the entrance of a commercial mosquito suction trap inside an insect rearing cage, with mosquitoes flying freely within the cage until they were sucked in by the trap, through the sensor, and into the catch bag within the trap. Each flight recording made by the sensor corresponded to a different mosquito. Five features were extracted from each recording and used with five different machine learning algorithms for classification of mosquito genus and sex.

One of the features used was wingbeat fundamental frequency, which has been used in many studies for insect characterization and classification [15, 16, 23, 25, 35, 38, 58]. Differences in reported values of wingbeat frequency between studies can be due to intrinsic and/or extrinsic variables such as size, parity status, age, and ambient conditions [16, 34, 36, 41, 46]. In this study, the wingbeat fundamental frequency feature gave a high accuracy in sex classification in both *Aedes* (95.5%) and *Culex* (98%), but it scored lower (67.3%) in genus classification.

As other studies have indicated [16, 18, 39, 43], the use of the wingbeat frequency alone as a feature to differentiate between taxonomical classes or other attributes of mosquito biology can be challenging due to overlap in wingbeat frequency distributions. To address this, other authors have used additional features (i.e., depolarization ratio) [16] or metadata (i.e., localization, environmental variables, and circadian rhythm) [18] in combination with fundamental frequency to improve their classification methods. In the present work, we have tested several features apart from or in combination with the fundamental frequency to better classify mosquito genus and sex.

The use of both fundamental frequency and fundamental peak power, yielded better performance in sex and genus classification than fundamental frequency alone. Although the effect of signal intensity or power has been investigated in mosquito mating and courtship behavioural experiments [46, 47], to the best of our knowledge, fundamental peak power has not been used as a feature in mosquito classification studies. In other sensor systems, the reported signal intensity or power may depend on the position and orientation of the flying mosquito with respect to the sensor [59], whilst our optical setup was designed to measure wingbeat power relatively independently of the position and orientation of the mosquito within the sensing volume.

Despite the better results obtained in this work using the fundamental frequency and power features in comparison with fundamental frequency alone, the more complex spectrogram and MFCC features provided the best performance for genus and sex classification. MFCCs are normally used in applications such as speech recognition [60] or music information retrieval [61] and although MFCCs are based on human perception of pitch, they have given good results in sound recognition studies with mosquitoes and other insects [34, 49, 62, 63].

In this study, the best performing machine learning algorithm depended on the classification task. For genus classification, DNN showed the best performance, with an accuracy of 94.2%, trained on the spectrogram feature. In another work [33], DNN also gave the best performance for genus classification between *Aedes* and *Culex*. For sex classification, the best performing algorithms and features were: LR with spectrogram or MFCC and GB with MFCC. Different machine learning algorithms were also compared for mosquito classification in a previous study [17] and it was concluded that the best algorithm for complex classification tasks was SVM. In our study, SVM had an accuracy of 93.4% for genus, although DNN, which was not studied in [17], performed slightly better (94.2%).

The classification of mosquito genus achieved a high accuracy of 94.2% while the classification of sex achieved 99.4% and 100% for *Aedes* and *Culex* respectively. Learning and validation accuracies in this work indicate that genus classification could possibly be improved with more training samples, and *Aedes* sex classification with more complex models and/or features. Other studies have successfully achieved automatic classification of genus [25, 33] and sex [16, 24] using machine learning with relatively large datasets [34] and placing emphasis on class balance [17]. However, only a small number of sensor studies have been done using a mosquito suction trap, either without an automatic classification system [43] or with only mosquito and non-mosquito counting and without differentiating mosquito genus and sex [64].

To our knowledge, we present the first sensor system for use with a commercial mosquito suction trap, which provides automatic classification of genus and sex with high performance, based on a large number of training samples, with class balance. Further work is needed to achieve mosquito species classification and to evaluate this system for field applications, which is of great importance for public health.

Conclusions

In this work, we have presented the results of a novel sensor system for genus and sex classification of *Aedes* and *Culex* mosquitoes captured by a commercial suction trap in laboratory conditions. The obtained results are encouraging for the use of the sensor with standard suction traps in the field, for the remote surveillance and classification of genus and sex of *Aedes* and *Culex* mosquitoes.

Declarations

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Availability of data and materials

The datasets generated during and/or analysed during the current study are not publicly available due to the protection of intellectual property defined under the H2020 agreement No. 853758, but are available from the corresponding author on reasonable request.

Authors' contributions

JE, ST and NB conceived and designed the study. JE, MW and PV designed and built the sensor. ST, NB and CA designed the entomological part of the study. JB and MG conducted the flight assays with the sensor. MG, NP and MV conducted mosquito rearing and maintenance and gave support on flight assays. BF conducted the feature extraction of flight assays and implemented the machine learning process to build the classification models. MG and BF analysed the results and drafted the manuscript. NB, MW, CA, ST and JE revised the manuscript. All authors read and approved the final manuscript.

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Competing interests

Irideon S.L. is currently applying for a patent relating to the content of the manuscript.

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Figures

Figure 1

a Prototype sensor (top) fitted to a BG-Mosquitaire trap (bottom); **b** Illustration of optical sensor basics. A LED (1) emits a diverging beam of light (2), which falls upon a lens (3) that form a collimated beam of light (4), which after a distance of 110 mm, falls upon a second lens (5) that forms a converging beam (6), which focuses onto a photodiode (7). When a mosquito (7) enters the collimated beam (4), it casts a shadow (8) upon the photodiode (7) i.e., the sensor employs the so-called optical extinction mode of operation. As the insect flaps its wings within the collimated beam (4), the light falling on the photodiode (7) is modulated, allowing

determination of various insect characteristics. Multiple optical emitter-receiver pairs are employed in the cylindrical sensing volume described; **c** Example of a recorded mosquito flight with ADC sample number (0 to 1023) on the x-axis and amplitude on the y-axis, scaled to a range of [-1, 1].

Fig.2

Figure 2

a Power spectral density (PSD) plot of a typical mosquito flight. The wingbeat fundamental peak is labelled as f_1 . The fundamental frequency is indicated by the vertical arrow and the fundamental peak power is indicated by the horizontal arrow. The various peaks to the right of f_1 are harmonics of f_1 , i.e. at frequencies of $2*f_1$, $3*f_1$ etc; **b** Scatterplot of wingbeat fundamental frequency and peak power for the full dataset showing *Aedes* genus in red and *Culex* in blue.

Fig.3

Figure 3

Representation of the machine learning classifications (in bold text), with their respective classes immediately below and indicated by the arrow heads.

Fig.4

Figure 4

MFCC generation.

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