Video and Sound Fusion by Feature Subset Selection in Insect Behavior Monitoring

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Abstract—This paper presents a new data-mining aproach of feature subset selection as a fusion technique to automatically and optimally configure an insects behavior identifier. It is accomplished by a fusion of video and sounds directly under the space of attributes. Harris detection was used as insect tracking, as well as Wavelet-Multifractal as sound analysis. In the case of Wavelet-Multifractal, it was tested more than one mother-wavelet, being Morlet the best. It was proposed wavelet modulus maximum to extract multifractal sound attributes for pattern recognition of an insect behavior. Wrapper data mining approach was used to select relevant attributes. It has been found that, in general, wavelet-multifractal-based schemes perform better for sound, particularly in terms of minimizing noise distortion influence. The image features only determine the mating and the soud attributes for others behaviors.

Index Terms— fusion, insect behavior, sound, video tracking, wavelet-multifractal.

1 Introduction

The scientific interest of investigating insects has great economic importance as beneficial organisms in agriculture and forestry (insects play significant role in the food chain of other species and the fertility of plants). However, a number of insect species also have negative contribution to agricultural economy as they constitute a threat to plants and crops [1].

Insects are mainly identified by their appearance and sound production that are species-specific. The detection and species recognition of insects are usually carried out manually, using trapping and observation methods [1].

Recent progress in computer technology as well as in signal processing and pattern recognition has introduced the possibility of automatically identifying species primarily on the basis of capturing subtle differences by means of video frames [2], [3], [4], [5] and [6], and acoustic signal processing [7], [8], [9], [10], [11] and [12].

Tracking objects can be complex due to loss of information caused by projection of the 3D world on a 2D image, noise in images, complex object motion, nonrigid or articulated nature of objects (insect legs and antennaes), partial and full object occlusions, complex object shapes, scene illumination changes, and real-time processing requirements [12].

At this work, insect movement and behaviour were monitored and analysed by computing mean values of the temporal movements during bioassays, saving the tracking for each insect.

The insect behavior is more complex. It could not be moving, but communicating all the time by bioacoustics signals. Acoustic identification of insects is based on their ability to generate sound either deliberately as a means of communication or as a by-product of eating, flight or locomotion. Provided that the bioacoustics signal produced by insects follows a consistent acoustical pattern that is species-specific, it can be employed for detection and identification purposes [1].

At the same time to video tracking, the behavior needs to be determined by acoustical signals too. There are a lot of acoustic signal processing techniques [1]. In the present contribution, we address a bioacoustic signal classification problem by exploiting wavelet-multifractal techniques, and afterwards successfully adapted for behavior system implementation.

The main goals of this work were study insects' behavior by fusion of videos and songs. Harris detector [13] was used to describe moving and wavelet-multifractal, to automatic detection of 3 different types of songs: Calling songs, species-specific songs used to call females from far away; Courtship songs, mostly used if male and female are close or preferably if they have antennal contact; and Aggressive songs, this type of song is used by one male telling all other males to keep their distance. Finally, the fusion was performed based on feature subset selection from a data-mining approach.

2 Review Methods

2.1 Video tracking

One of the most intuitive algorithms to detect moving objects is the method of subtraction of consecutive frames in a video [14]. They are very sensitive to noise and lighting changes. When the number of frames in the sequence is large and there is little change between consecutive frames, then the modeling of the background is most appropriate. This technique is widely used in the context of security applications, when the camera is fixed, and is classified as predictive or not predictive methods. Some variations can be considered, based on the subtraction of the current frame from a standard frame, obtained before the start of detection, until the last subtraction of successive frames. The mixture of Gaussians is the detection method based on modeling the background scene that stands out. Variations of these functions using Gaussian mixtures appear in many applications [15].

Optical flow detection is the most cited in the literature [16] and [17]. Detectors for salient points have been recently the most cited, and include Harris detector and SIFT transform

(Scale Invariant Feature Transform) [18]. The approach of these detectors is to extract the corners or salient points in each video frame, followed by a matching algorithm to trace detected points in successive frames.

It was used in this work the Harris detector as described in next section.

2.2 Harris Detector

The Harris corner detector [13] is based on the covariance matrix and the examination of its eigenvalues. This detector is calculated quickly and efficiently for each pixel.

Let the motion estimation function *E (u, v)* for a movement *[u, v]* of a point *(x, y)* in the image *I (x, y)*, defined in (1):

$$E(u,v)=\sum_{x,y} w(x,y)[I(x+u,y+v)-I(x,y)]^2 \tag{1}$$

where *w(x,y)* is weight function at *(x,y)* and *I(x+u,y+v)* the image after moving *[u,v]*.

The weight function is defined as a Gaussian (2):

$$G(x,y,\sigma)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

For small *[u,v]*, by Taylor expansion (3):

$$E(u,v)\cong\begin{bmatrix}u & v\end{bmatrix}M\begin{bmatrix}u\\ v\end{bmatrix} \tag{3}$$

where M is 2x2 covariance matrix from image (4):

$$M=\sum_{x,y} w(x,y)\begin{bmatrix}I_x^2 & I_xI_y\\ I_xI_y & I_y^2\end{bmatrix} \tag{4}$$

By autovalues of M, is determined λ_1 and λ_2, representing the best and least changes of *E(u,v)*.

The corner region R (5) is:

$$R=\det M-k(traceM)^2 \tag{5}$$

where:

$$\det M=\lambda_1\lambda_2 \tag{6}$$

$$traceM=\lambda_1+\lambda_2 \tag{7}$$

and k = 0.04-0.06 is an empirical constant.

The Harris algorithm is:

- *Find all R > thresholding;*
- *Determine points with local maximum of R.*

2.3 Wavelet Transform

The Wavelet Transform technique consists of a window variable that allows the use of a time window to analyze low-frequency information, more accurately, and a small window for high-frequency information [19].

According to [19], it is defined the family of wavelet functions *Ψa,b(t)* , as in equation (8):

$$\psi_{a,b}(t)=|a|^{-\frac{1}{2}}\psi\left(\frac{t-b}{a}\right)\qquad a,b\in\Re,\qquad a\neq 0 \tag{8}$$

where, t represents time variable or space, generated from the operations of expansion (a scale factor) and translation (b factor) of the same complex function, which is the mother wavelet.

The wavelet analysis uses a prototype function called mother wavelet that has zero mean and is an oscillating function in a central part, i.e., decays to zero on both sides. Mathematically, the Continuous Wavelet Transform (TWC) of a given signal x(t) in relation to the mother-wavelet *Ψ(t)* is defined by (9):

$$TWC(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{9}$$

being, a the dilation or scale factor, b the translation factor, and these variables are continuous.

Consequently, can be all the characteristics of a particular sign [19], [20].

The wavelet transform modulus maximum (MMWT) method [21] consists in changing the continuous sum over space in equation into a discrete sum over the local maxima of *TWC(x,a)* considered as a function of x.

The modulus maximum is found from the original TWC using a simple algorithm that traverses the Wavelet scalogram, scale by scale and identifies the local maxima and minima [21].

2.4 Multifractal

The multifractal formalism has been introduced to provide a statistical description of singular measures in terms of thermodynamic functions such as the generalized fractal dimension *Dq* and the *f(α)* sigularity spectrum [14]. Several numerical methods have been proposed to calculate these quantities. In this paper it is shown the method based on canonical mehtod proposed by [15].

Covering the support of the mesure μ of a song with box of size δ and define $P_i(\delta)$ to be the probability in the *ith* box, it is defined an exponent (singularity strength) as the equation (10):

$$P_i(\delta)\sim\delta^{\alpha_i} \tag{10}$$

If it is counted the number of boxes *N(α)* where the probability P_i has singularity strength between α and *α+dα*, then *f(α)* can be defined as the fractal dimension of the set of boxes with singularity strength α by equation (11):

$$N_\delta(\alpha)\sim\delta^{-f(\alpha)} \tag{11}$$

where the function *f(α)* possesses the properties of a dimension and represents the singularity spectrum. Homogeneous measures are characterized by singularity spectrum supported by a single point (α_0 , $f(\alpha_0)$). Multifractal measures involve singularities of different strengh, in this case the *f(α)* spectrum has generally a single humped shape wich extends over a finite interval [α_{min}, α_{max}], where α_{min} corresponds to the strongest singularity, and $\alpha_{\max}$ corresponds to the weakest singularity.

The normalized measure $\mu(q,\delta)$ is constructed, where the probability in the boxes of size δ are (12):

$$\mu_i(q,\delta)=\frac{[P_i(\delta)]^q}{\sum_j[P_j(\delta)]^q} \tag{12}$$

Being q the order moment of a statistic distribution with q_s within the interval [-∞ ∞]. When $q < 0$, μ emphasize regions in the distribution with less concentration of a measure, whereas the opposite is true for $q > 0$ [22].

The generalized fractal dimension D_q , which correspond to scaling exponents for the *qth* moments of measure μ, gives the singularity or the multifractal measure.

Defining a partition function (13):

$$Z_q(\delta)=\sum_{i=1}^{N(\delta)}\mu_i^q(\delta) \tag{13}$$

Where q is the statistical distribution of moment. The partition function Z_q, is related with the escale δ by (14):

$$Z_q(\delta) \sim \delta^{-\tau(q)} \quad (14)$$

By [21]:

$$D_q = \tau(q)/(q-1) \quad (15)$$

$$\propto(q) = \frac{d\tau(q)}{dq} \quad (16)$$

$$f(\propto(q)) = \tau(q) - \propto(q)q \quad (17)$$

Thus the singularity spectrum *f(α)* is obtained by Legendre transform $\tau(q)$. To avoid distortions from Legendre, in [22] it was proposed a canonical method, based in equations (18) e (19) to determine the singularity *f(α)* and *α*.

$$f(\propto(q)) = \lim_{\delta\to 0} \frac{\sum_{i=1}^{N(\delta)} \mu_i^q \log \mu_i^q}{\log\delta} \quad (18)$$

$$\propto(q) = \lim_{\delta\to 0} \frac{\sum_{i=1}^{N(\delta)} P_i^q \log \mu_i^q}{\log\delta} \quad (19)$$

A multifractal set can be completely described either by an infinite number of generalized dimensions or by the singularity spectrum. The generalized fractal dimension is defined as (20):

$$D_q = \frac{1}{q-1} \lim_{\delta\to 0} \frac{\log \mu(q,\delta)}{\log\delta} = \frac{1}{q-1} \lim_{\delta\to 0} \frac{\log \sum_{i=1}^{N(\delta)} \mu_i^q}{\log\delta} \quad (20)$$

The *Dq* is related to the system geometry and multifractal spectrum *f(α)* to thermodynamics parameters of the system, where *f(α)* e *α* are the entropy and the internal energy of the system, respectively. The multifractal *f(α)* have the capability to describe physically the system.

A fractal dimension *D(q=0)* or D_0 is a global dimension and gives the mean of the system, *D(q=1)* or D_1 is the information dimension and is related to Shannon entropy. For D_1 near to 1,0 the system is uniform for all scales and for D_1 near 0 gives a subset of scales in which the irregularities are concentrated. *D(q=2)* or D_2 is the mesure correlation for δ intervals. The relation between D_0, D_1 *e* D_2 is defined as (21).

$$D2 \le D1 \le D0 \quad (21)$$

and $D_0 = D_1 = D_2$ fractal is self-similar and homogeneous. And the definitions of them are in (22) to (24).

$$D_0 = \lim_{\delta\to 0} \frac{\log(N(\delta))}{\log\delta} \quad (22)$$

$$D_1 = \lim_{\delta\to 0} \frac{\sum_{i=1}^{N(\delta)} \mu_{ii}(\delta)\log(\mu(\delta_i))}{\log\delta} \quad (23)$$

$$D_2 = \lim_{\delta\to 0} \frac{\log(C(\delta))}{\log\delta} \quad (24)$$

where *C(δ) is* a correlation function.

To use Wavelet it is necessary to rewrite the canonical equations. The Hölder exponent for function *x(t)* is the singularity *α*. It is defined as the largest exponent such that exists a polynomial $P_n(t)$ of order *n* satisfying (25):

$$|x(t) - P_n(t-t_0)| \le C|t-t_0|^{\propto} \quad (25)$$

for *t* in a neighborhood of t_0. The polynomial $P_n(t)$ corresponds to the *Taylor* series of *x* around $t=t_0$. Thus the exponent measure the regularity of a function *x(t)* in the point t_0. The higher the exponent $\alpha(t_0)$, the more regular is the function *x(t)*.

Using a local TWC defined by equation (9), where *b=t0*, then (26):

$$TWC(t_0,a) \sim a^{\alpha(t_0)} \quad (26)$$

where $\alpha(t_0)$ is the singularity exponent behind t_0.

Using MMTW instead of the TWC, so the partition function becomes (27):

$$Z_q(a) = \sum_{i=1}^{N(\delta)} |MMTW(a,t_i(a))|^q \approx a^{\tau(q)} \quad (27)$$

From [22], the normalized measure μ is rewrite as (28):

$$\mu(q,a,t_0) = \frac{|MMTW(a,t_i)|^q}{\sum |MMTW(a,t_i)|^q} \quad (28)$$

where MMTW defined in escale a.

Finally, the singularity spectrum is defined by equations (29) and (30):

$$\propto(q) = \lim_{a\to 0} \frac{\sum_{i=1}^{t_i(a)} \mu_{ti}^q \log|MMTW(a,t_i)|}{\log a} \quad (29)$$

$$f(\propto(q)) = \lim_{a\to 0} \frac{\sum_{i=1}^{t_i(a)} \mu_{ti}^q \log \mu_{t_i}^q}{\log a} \quad (30)$$

In the Figure 1 was shown (a) a sound from a male insect and (b) the TWC escalogram with representation of MMWT in black lines.

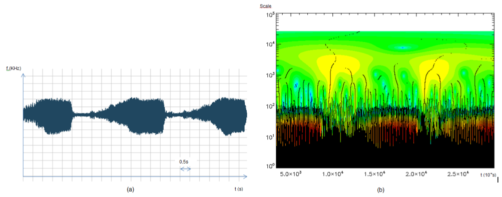


Figure 1. (a) male insect sound and (b) TWC scalogram with MMWT represented

3 Fusion Proposal

There are three levels of fusion: data fusion, feature fusion and decision fusion. Feature level fusion was chosen over the other forms of fusion for a variety of reasons. The most important of these is that, unlike the others, there are different fonts of datas: soud and video. The obvious practical reason aside, feature level fusion does have many desirable qualities in a feature subset selection method. Big features not indicate a better solution and it is necessary to select only the relevant features.

In this work, at the same time are acquired sonds and videos from a biassay. Spectrogram was generated for each sound. Selecting main partes of them was applied Wavelet Transform to construct the scalogram. With multifractal analysis was performed the singularity spectrum and sound attributes were determined. By the other side, each frame of video were analysed and applied Harris detector to determine corner points. The euclidean distance was used to choose the right salient points used to determine tracking of insects. Once the tracking is performed some attributes of moving were saved in a database and finally was applyied a fusion method.

3.1 INSECTS

All experiments were conducted on adult stink bugs of the species of the *Euschistus heros* from laboratory colonies started from adults and nymphs collected on soybean fields near Brazilia, DF, Brazil. Males and females, at Embrapa Research Institute in Brazilia in an environmental room at 26.0±1.0C and 60±10% RH, under an LD 14-10 h photoperiod with lighting provided by 16 fluorescent lights of 40 W.

Vibratory signals emitted by males and females in their temporal and spectral characteristics were recorded from virgin and sexually mature bugs using a loudspeaker with a microphone amplifier (Sonifex Redbox, RB-MA1); and home-made operational amplifier, digitized (Aardvark-Direct Pro 24/96) and stored on a computer.

In Figure 2(a) is a typical pentatomid female calling [23]. Figure 2(b) is an irregular female songs observed when male is not present, Figure 2(c) is a male song after female answer, Figure 2(d) male song after some time without female songs and Figure 2(e) male song when there is more males togheter the female and Figure 2(f) male songs during head-butting or when following the unreceptive female [19].

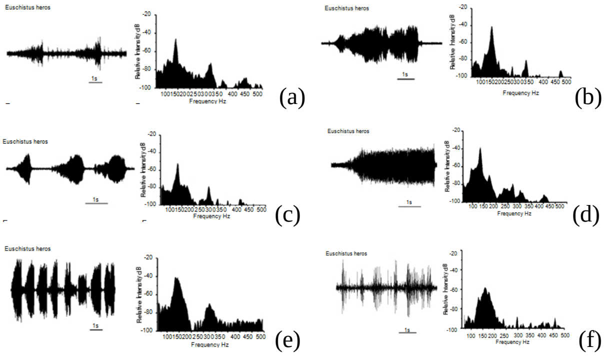


Figure 2. Songs repertoires of the *Euschistus heros* from [23]: (a) and (b) female songs, (c) and (d) male songs, and (e) male rivality (f) male after unreceptive female.

3.2 FEATURE VECTOR

Tracking features

It was released insects in the release area of the arena and recorded its movements from above using a video system with a video camcorder Sony. A video frame grabber (Pinnacle System) digitalized the analogue video signals from the camera, and the data were processed. From video, it was record the position of the insect at preset time intervals and processed the analysis of different behavioural parameters. The parameters defined are: linear displacement *(dx)*, linear velocity *(v)*, angular velocity *(w)*, turning rate *(dw)* and tortuosity *(T)*. They were the tracking features extracted from videos and used as part of feature vector.

Insect movement and behaviour were monitored and analysed by computing the linear velocity (mm/s), linear displacement (mm), angular velocity (grade/s) ,turning rate (number of directional changes/s) and tortuosity of insects that moved in the olfactometer. Tortuosity was measured using the tortuosity index, which quantifies insect kinetic movement by equation (31).

$$T = 1 - m_p / t_l \tag{31}$$

Where m_p is the projection of the track in the general straight line, and t_l is the total length of the track defined by (32). The index varies from 0 (zero) for minimal tortuosity to 1 (one) for maximal tortuosity.

$$t_l = \sum \left\| x_i - x_{i+1} \right\| \tag{32}$$

Where x_i is the position in a time and x_{i+1} the next position. It was performed 30 replicates for each phase to be monitored togheter the accustical signals.

Sound Features

For songs, it was selected typical sounds of male and female insects when occurring: calling, courtship and aggressive songs [24], 30 samples for each one. The spectrogram, TWC scalogram by different mother-wavelet (Paul, Morlet, Gauss, Mexicam Hat and Shanon) [20], MMWT, and graphs *f(□)* x □ representing a multifractal spectrum was obtained for each behavior. The singularity spectrum was represented by *Δf, Δfmáx, Δfmin* to see the symmetry of the curve, the Hölder coefficient □, the fractal dimension D_0, D_1 and D_2, related to auto-similarity, entropy and correlation, respectively.

A characteristic sound vector *(Vc)* was determined for each insect analyzed, as the equation (33):

$$V_c = \begin{bmatrix} \Delta q; \Delta f; \Delta f_{\max}; \Delta f_{\min}; \alpha_{\max}; \alpha_{\min}; \Delta\alpha; \\ f(0) - f(-1); f(0) - f(1); \alpha(0) - \alpha(-1); D_0; D_1; D_2 \end{bmatrix} \tag{33}$$

3.3 FEATURE SUBSET SELECTION

Feature selection methods generally reduce the dimensionality of a problem domain for the purposes of improving the performance of Data-mining algorithms and to decrease the computational load of applying the processing feature selection is often viewed as a search problem in a space of feature subsets. On one hand, filter methods use an evaluation function that relies solely on properties of the data, thus is independent on any particular learning algorithm. On the other hand, wrapper methods use the inductive algorithm to estimate the value of a given subset [25]. An induction algorithm is typically presented with a set of training instances, where each instance is described by a vector of features or attributes values and a class label. The task of the induction algorithm (inducer) is to induce from training data a classifier that will be useful in classifying future cases. The classifier is a mapping from the space of feature values to the set of class values. In the feature subset selection problems, a learning algorithm is faced with the problem of selecting some subset of features upon which to focus its attention, while ignoring the rest. In fact non-intuitive results have been demonstrated that show that the inclusion/exclusion of ‘‘irrelevant’’ or correlated feature may improve the performance of an induction algorithm while harming the performance of another algorithm. Interactive methods to search for suitable sets of features have been proposed and have found success especially in unsupervised learning. In this case the user is acting as the wrapper and directing the search process based on their expertise in the problem domain. The idea behind the wrapper approach [25] is simple: the induction algorithm is used as a black box. For each selected feature subset during the search process, one classifier is created by the learning algorithm. Typically, the accuracy of this classifier is used evaluate the feature subset efficiency. Therefore, the selected subset is relevant to the learning task and the algorithm [25].

Practical machine learning algorithms i.e. decision tree algorithms such as C4.5 [26], and instance based algorithms such as IBL [26] have shown lower classification performance when induced from sets with a lot of irrelevant features. Thus, the feature subset selection can improve the accuracy of classifiers induced by the same algorithm used in wrapper method. In the supervised learning, in general, it is attempting to minimize misclassification or some loss function based on accuracy, recall or precision. In this case an automatic search through the space of solutions is useful and can incorporate, as a starting point, the results of the user's knowledge, gained through experience or discovered by interactively searching the solution space.

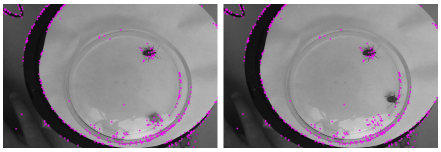
Wrapper methods are widely recognized as a superior alternative in supervised learning problems, since by employing the inductive algorithm to evaluate alternatives they have into account the particular biases of the algorithm. However, even for algorithms that exhibits a moderate complexity, the number of executions that the search process requires results in a high computational cost, especially as it is possible to shift to more exhaustive search strategies.

In this work, it was used wrapper with an exhaustive search by C4.5 algorithm. It was used too Greedy Stepwise search, in order to reduce the processing time.

4 Results

4.1 Video Tracking

The main problem in tracking system is the illumination. At the first time it was used a fluorescent illumination. But this kind of light presents flickering problems resulting in a lot of wrong movent in the detector. In Figure 3 is possible to see the corners detected before and after movement. Only insects moved in this video, and the others points detected were light effects. In spit of that, when using successive frames subtraction to define a region of probability of movements and corner detector it was possible to select only the main vector representing a bug movent to trace the rote. Some time it fails too, but in general it was possible to have good results.



(a) (b)

Figure 3. Sequence frames from a video after salient point detection by Harris detector. (a) intant t_0 and (b) t_0+1

In Figure 4 was shown a matching with all points detected without filtering regions. Therfore, when insects move antennas and legs, it could not be considered movement. It was solved this kind of bugs, defining a smoothing filter preprocess the images before movement detection.

The number of tracking attributes is not big. The feature selection was made when sound attributes was joined to them.

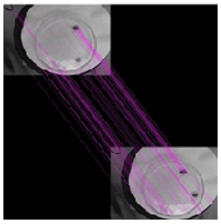
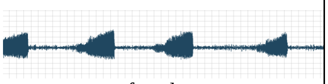
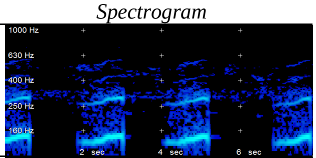
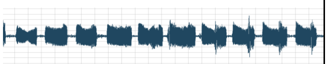
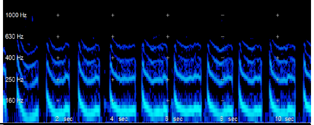
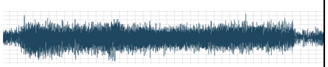
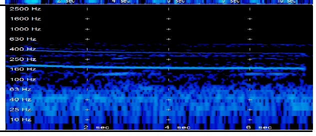


Figure 4. Matching corner points to detect movement.

4.2 Sonds

For all signals it was ploted the spectrogram that identifies all insect frequencies. It is possible to observe some examples of songs and the spectrogram determined for male and female insectcs in Table 1.

TABLE 1: Wavelet scalogram and their multifractal spectrum

Original songs	*Spectrogram*
 female	
 Male Rivality	
 Male	

Diferrent mother-wavelet was processed and analysed. In [22] it is the description of selected mother-wavelets in this work: Morlet, Gaussian, Gaussian 4th derivated, Mexicam hat, Shanon and Paul.

It was observed that for a complet range of q, $-2<q<2$, steps 0.1 more then one kind of mother-wavelet is ok to perform multifractal analysis. It was choosen the Morlet and Paul as those presented more complet multifractal spectrum, i.e., ranges from $q<0$ to $q>0$.

In Table 2, it is shown the wavelet scalogram determined and results for fractal analysis, the multifractal spectrum. In the female case, the punctual spectrum showed that are more homogeneous compared to the male, which may be indicative of the different "sounds" emitted by males during the breeding call, and even the territoriality function. There were analysed parts of signal and a complete on in a time.

By TWC scalogram and MMWT, was plotted $f(\alpha)$ x α graphs representing a multifractal spectrum for each behavior. Those analyses were made for 30 samples of each one. At the same time, video tracking attributes were collected.

Multifractal analysis indicate that the values of $\Delta\alpha$ are higher emissions for isolated insects males or females and, therefore, in the case of mixed mating and rivalry, have a greater degree of multifractal, i.e., the system is more chaotic than for separate issues. Depending on the behavior issues observed in videos when there is more stress for absence of one partner, male or female, more then one male or when female refused a courtship, the multifractal analysis indicate the system in changing, more entropical.

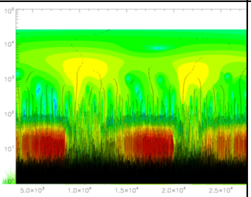
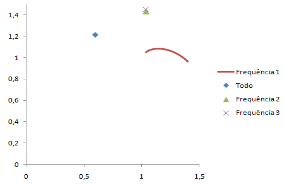
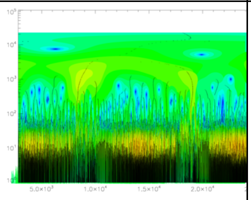
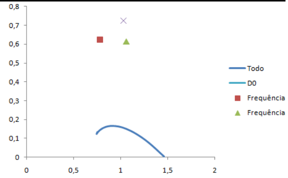
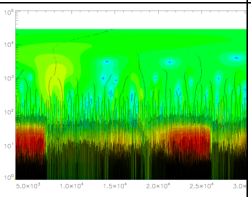
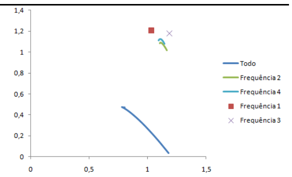
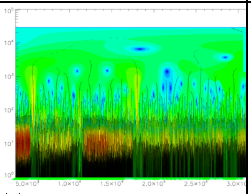
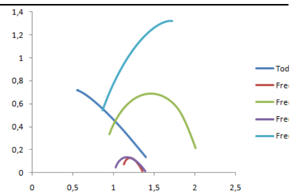
4.3 Experiments

This work was divided in two experiments: First, fusion of sound and tracking using sound attributes from equation (33) plus all video attributes; Second, instead of sound attributes from equation (33) it was used a complete singularity spectrum f(□) x □, for interval -2<q<2, with step 0.1 plus all video attributes.

The idea here was to study the use of a complete singularity graph with all values of q, or identify the better parameters that describe the multifractal autosimilarities.

The proposed method has been tested on a wide variety of conditions. The proposed selection of attributes using wrapper with exhaustive (when impossible, Greedy Stepwise search), C4.5 algorithm was applied to both vector of characteristics. The exhaustive search has algorithm complexity O(2n), where n is the number of features corresponding to 41 (sound) + 5 (tracking) and 14 (sound) + 5(tracking) for the first and second experiments, respectivelly. The fusion of attributes was made by feature subset selection to obtain the most relevants attributes in behavior of insects.

TABLE 2: Wavelet scalogram and their multifractal spectrum

Insect song	*Wavelet scalogram (scale x time)*	*Multifractal Spectrum f(α) x α*
Male	 (a)	 (b)
Female	 (c)	 (d)
Courtship	 (e)	 (f)
Rivality	 (g)	 (h)

The precision obtained with the best feature subset was 99.62% (10-fold cross-validation). For all experiments it was used 10 folds cross-validation.

The results could be observed in Table 3.The use of wrapper approach improve the correct classification.

TABLE 3: Results of analyzes with all attributes and a subset selection of attributes

	Experiments			
	First	*Second*	*First w/ wrapper*	*Second w/ wrapper*
Correctly classified instances	67.37%	39.07%	80,99%	97.61%
Mean error	0.25%	0.47%	0.15%	0.01%

The correct classification did not result in a good precision for all classes. The Table 4 has the values obtained for precision each class of analysis, i.e. male, female, rivality or courtship classes. The class that had better classification could be observed in Table 4. The rivality is where there is more multifractal complete description and better results.

TABLE 4: Precision of class's classification

	First Exeriment			
	male	female	rivality	Courtship
With wrapper	59.9	45.1	67.1	27.9
Without wrapper	68.3	55.2	87.8	37.1
	Second Experiment			
With wrapper	88.43	78.23	99.1	98.3
Without wrapper	40.1	65.2	75.2	65.7

The first experiments with Wrapper, selected α(q=-1.6), α(q=1.7), f(α(q=-2), f(α(q=1.8) and the second experiment, the caracteristics Δf, Δfmax, Δfmin, f(0)-f(-1), α(0)-α(-1). Is it possible to observe that video attributes did not selected and it was reduced a lot the number of attributes.

Just only one case it was selected Tortuosity parameter. However, is was discarded here because the precision for male, female and courtship times analysis was less than 40%. Only rivality was classified with 57.7%, with wrapper approach.

It was selected only small times where the insectcs was singing or in a calling way or in a rivality way. As the analysis need much more time, it is necessary much more processing time and better machines to perform a complete analysis.

5 Conclusion

The evolution of the chemical ecology was accelerated in the last decade with the coming of emergent technologies of instrumentation for analysis and for diagnoses. In that way, this work presents the software methodology for analysis of behavior of insects through images and sounds for studies of the sense of smell of insects. The principal result of this system, until now, is the obtaining of the consistent evaluation way of the behavior of the insects. Thus, it can be determined the composition of a pheromone mixture that induces modification in the behavior of the white insect, be in the attraction and sexual intercourse, be aggregation or dispersion.

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