Features Extraction Applied to the Analysis of the Sounds Emitted by Honey Bees in a Beehive

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***Abstract*—Last years increase in bee mortality has underlined the necessity of an intensive bee hive monitoring in order to better understand the problems which are seriously affecting the honey bee health. Sound emitted inside a beehive is one of the key parameters for a non-invasive monitoring of their health condition. In this context, the proposed work aims at analyzing the bees' sound introducing features extraction useful for sound classification techniques and for determine dangerous situations. Several experiments on a real scenario have been performed focusing on orphaned colony case and highlighting the potentiality of the proposed approach.**

I. Introduction

The importance of honey bees is not limited to the production of honey, beeswax, royal jelly and propolis. In fact these insects play a key role in the service of pollination allowing the proliferation of both cultivated and spontaneous flora. Recent years have seen an increase in bee mortality which can result in a loss of pollination services, with serious ecological and economical consequences. The causes can be found in the Colony Collapse Disorder (CCD) which is a situation characterized by a sudden disappearance of honey bees from the hive [1]. Many bee scientists agree that the decline of honey bee colonies is the result of multiple stressors, acting independently, in combination, or synergistically to impact honey bees' health [1], [2]. Starting from these aspects, the necessity of an intensive monitoring activity of honey bees emerges clearly, in order to understand the problems and the causes of bees' mortality. In this context, sound analysis provides the possibility of obtaining a non-invasive tool for honey bee health monitoring. Sounds are used by the bees to communicate within the colony [3], [4], and an accurate interpretation of these sounds could lead to the identification of specific situations. The sound is generated through vibroacoustic signal production that includes gross body movements, wing movements, high-frequency muscle contractions without wing movements, and pressing the thorax against the substrates or another bee [5]–[7]. Sound signal modulates many colony behaviour and it has been proved that there is a strict correlation between the frequencies and the amplitudes of honey bee hive sounds and the prevision of events like swarming [8]–[11], the presence of airborne toxic in the hive [12], the presence of a young queen inside the hive [5], [6], [13] and presence or absence of the queen inside the colony [7]. Regarding the honey bee sound analysis, few approaches can be found in the literature. In [11], a sound-based beehive monitoring is presented. The recorded sound is first analyzed by means of short time Fourier transform, and then some spectral indicators such as peak frequency, have been used with principal component analysis and support vector machine for varroa-mite detection. In [10], a spectrogram-based sound analysis has been used for early detection of swarming, showing an increment in low frequency spectrum produced by honey bees before this event. Frequency analysis has also been used for monitoring wagging dances as reported in [4]. They explain the correlation between bees dance and the presence of harmonics near 320 Hz in the recorded signals, showing that it is possible to generate signals at which bees react. In [14] a machine learning algorithm has been developed for the identification of bee buzzing from cricket chirping and ambient noise.

In [15], a machine learning method to automatically recognize the presence of queen bee in a hive using audio as input was proposed. This approach was based both on support vector machines and convolutional neural networks applied to the identification of queen bee presence. This study has shown the importance of features extraction before classification operation (e.g., Convolutional Neural Networks (CNNs) and support vector machine (SVM)) [15]. Therefore, the proposed work aims at investigating the application of some techniques for honey bee sounds' feature extraction. Starting from a well known techniques, such as short time Fourier transform (STFT) [16] and mel frequency cepstral coefficients (MFCCs) [17], a method based on Wavelet decomposition [18] and Hilbert-Huang transform [19] is presented and analyzed with real data. Several experiments have been performed using sound signals acquired by a multi-sensor platform developed in [20], [21] and installed in a real scenario.

The paper is organized as follows. Section II shows the proposed approaches and the developed algorithms for sound analysis. Section III shows experimental results, obtained analyzing recorded data from acquisition system of [20]. Finally, conclusions and future works are reported in Section IV.

II. Proposed Approach

The objective of the proposed work is the introduction of an effective features extraction procedure capable of determining useful information in the analysis of the sound generated in a

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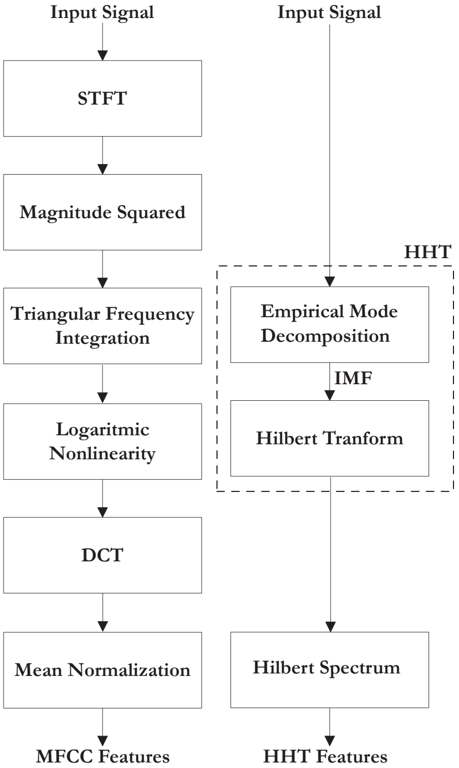


Fig. 1: MFCC and HHT Feature Extraction procedure.

hive. In what follows, five approaches will be considered and tested on a real scenario.

First of all, spectrogram analysis has been considered following [17]. It allows a visual representation of the signal, showing its spectral contents as it varies with time. As reported in [16], spectrogram is based on STFT, i.e., the signal is first windowed by means of a sliding time window then each frame is frequency transformed through fast Fourier transform (FFT).

Then, another important feature extraction technique considered is based on MFCCs. A first application of this feature in the case of bee sound classification can be found in [15]. As reported in [17], MFCCs are computed starting from the signal power spectrum, then the power spectrum is filtered through a triangular filterbank and then the energy on each subband is computed. Finally the discrete cosine transform of the logarithm of each energy value is evaluated, keeping only a defined number of coefficients as reported in Fig. 1. For this application, a number of thirteen coefficients has been considered.

Starting from these well-known techniques, three other approaches have been considered and applied for the first time to the beehive analysis. The first feature map is based on Hilbert Huang transform (HHT) [19], that is an algorithm for time-frequency signal analysis based on empirical mode decomposition (EMD). The HHT can represent the signal as a superimposition of basis functions called intrinsic mode functions (IMF) that are obtained through an adaptive procedure applied to the original signal. Each intrinsic mode function represents a simple oscillation that can be defined by the following properties: (A) The number of extrema and the number of zero-crossings must be either equal or differ at most by one extrema. (B) The mean value of the envelope defined by the local maxima and the local minima is zero. Starting from this assumption, a procedure for IMF estimation can be derived as described in [19]. At the end of the process, the original signal $x(n)$ can be reconstructed as a superimposition of M IMFs plus a residue, i.e.,

$$x(n) = \sum_{j=1}^{M} c_j(n) + r(n) \tag{1}$$

where $c_j(n)$ are the intrinsic mode functions. The process is stopped when the residue $r(n)$ becomes a monotonic function, or when the amplitude value is less then a predetermined value.

Once the signal has been decomposed, the Hilbert Transform [22] is applied to each IMF and used for the estimation of the analytic signal $a_j(n)$ as follows:

$$a_j(n) = c_j(n) + j\mathcal{H}\{c_j(n)\} \tag{2}$$

where $\mathcal{H}$ indicates the Hilbert transform with $j = 1, \ldots, M$. Then, equation (2) can be expressed in polar coordinates, i.e., $a_j(n) = A_j(n)e^{i\phi_j(n)}$ where $A_j(n)$ is the instantaneous amplitude of the signal, and $\phi_j(n)$ is the phase from which the instantaneous frequency can be derived according to:

$$f_j(n) = \frac{f_s}{2\pi}\big[\phi_j(n+1) - \phi_j(n)\big]. \tag{3}$$

The result is a time-frequency distribution of a signal that has its own amplitude, designated as the Hilbert spectrum $H_j(w, n)$. A diagram of the whole procedure is reported in Fig. 1. Finally for each j-th Hilbert spectrum, the vectors $f_j(n)$ and $A_j(n)$ are sorted as a function of increasing frequency, obtaining a spectral representation which is function only of frequency and amplitude. Now the feature can be represented in a three dimensional map where for each IMF the spectral content is clearly visible. HHT has already been applied in [15], but in a slightly different manner. Only the main frequency component from every Hilbert Spectrum has been extracted, and it has been used only in combination with MFCC to improve support vector machine results.

The other two approaches here proposed are based on wavelet transform (WT). Wavelets are mathematical functions that split data into different frequency components with the possibility to study each component with a resolution matched to its scale. WT decomposes the signal by means of properly time and amplitude shifted basis functions called mother wavelet. WT is a powerful instrument when signals are highly non stationary with power amplitude at many different frequencies as in our case. The wavelet transform is defined by the following formula:

$$X(s, u) = \frac{1}{\sqrt{|\, s \,|}} \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-u}{s}\right) dt, \tag{4}$$

where s is the scale index, u the wavelet temporal index, ψ is the mother wavelet, t is the signal temporal index and

x is the analyzed signal. Variation of scale index is related to the signal frequencies, i.e., an higher scale value means a dilated wavelet which approximate well low frequencies, while low scale value means a compressed wavelet which is closer to high frequencies. Compared to Fourier analysis that uses as basis functions only cosine, wavelet transform can use a variety of mother wavelet with specific characteristic, and the right choice is left to the user in function of the type of signal that has to be analyzed. When a signal is analyzed by means of WT, a graphic time-frequency representation can be derived using the square module of the transformed signal, i.e.,

$$S(s,u) = \frac{1}{\mid s \mid} \left| \int_{-\infty}^{+\infty} x(t)\psi^* \left(\frac{t-u}{s} \right) dt \right|^2 , \qquad (5)$$

where $S(u,s)$ is defined as *scalogram*. In Eqs. (4) and (5) index u and s change continuously realizing the continuous wavelet transform (CWT). CWT is a well known approach already used for feature extraction of animal sound [23], e.g., for analysis of sound emitted by Vespertilionidi [24] but never used for honey bee. As described in [25], Morlet wavelet is a well suited methodology for analysis of speech and sound since it generates a representation which is close to human perception [26]. As in the Fourier transform, the continuous transform of (4) and (5) can be discretized, limiting s and u to a finite set of value for the scale and time index according to:

$$\begin{cases} s = s_0^{-m}, & \text{with } s_0 > 1,\ m \in \mathbf{Z} \\ u = n u_0 s_0^{-m}, & \text{with } u_0 > 0,\ n \in \mathbf{Z}. \end{cases} \qquad (6)$$

This is call discrete wavelet transform (DWT). DWT as the CWT is well-known instrument for sound analysis and feature extraction. Several works have already shown the capability of using discrete wavelet for animal sound classification [23], [27]. The discrete wavelet transform is implementable by means of a three structure filter bank as the one reported in Fig. 2. This filter bank introduces a non uniform decimation on the signal improving the resolution on lower frequencies, implementing a multiresolution analysis. Each decomposition level generates two distinct outputs: the detailed coefficients, i.e., the output of the high-pass filter, and the approximation coefficients, i.e., the output of the low-pass filter. These coefficients are stored, while the approximation coefficients are used as input for the next decomposition level. Since the taps for the low-pass and high-pass filter are generated from the mother wavelet [28], the output of the filter bank correspond to the output of the discrete wavelet transform. Due to non uniform decimation, each wavelet coefficient vector has a different length. In order to obtain a more clear graphic representation, each DWT coefficients have been properly interpolated replicating its samples and thus obtaining a set of uniform length vectors with the same length of the input signal. For this work, a ten level filter bank has been used obtaining eleven coefficients (i.e., ten detailed coefficients and one approximation coefficients). For the mother wavelet many different wavelet families have been tested and then the

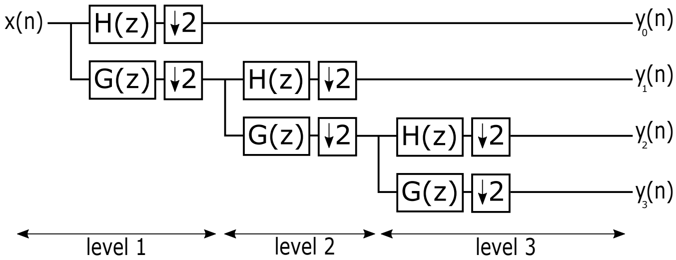
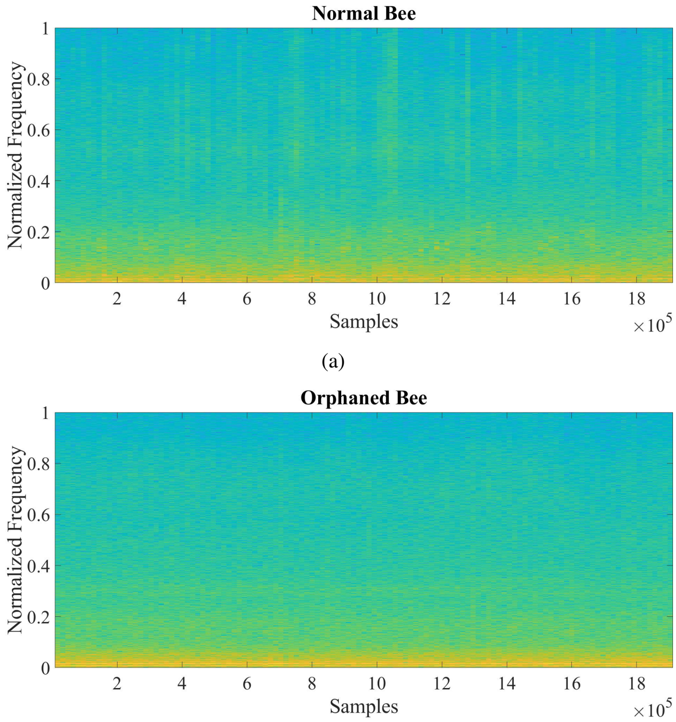


Fig. 2: A 3-Level asymmetric dyadic analysis filter Bank. $G(z)$ and $H(z)$ are respectively the low-pass and the high-pass filters derived from the mother wavelet.



(a)

(b)

Fig. 3: Spectrogram of the sound generated in the beehive considering one minute recording. In particular, panel (a) shows data from a normal colony, on the 8 May 2018 at 12.30, while panel (b) shows data from the same colony without the queen bee on the 13 July 2017 at 12.30.

discrete Meyer [29] has been selected due to its results with the analyzed signals.

III. Experimental Results

A. Data Acquisition

For the experimental results data from the NU-Hive project database have been used [20]. The sounds used for the experiments have been recorded in the same colony, taking into considerations two different days. The first one is from the orphaned colony, i.e., the queen is dead, the other one came from a normal day of the same colony. Data have

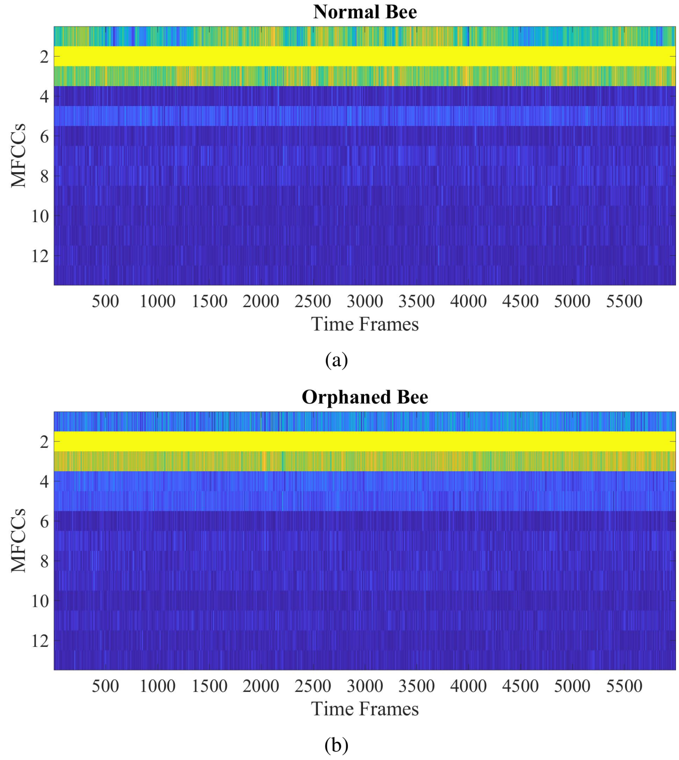


Fig. 4: Features extraction exploiting mel frequency cepstral coefficients approach.

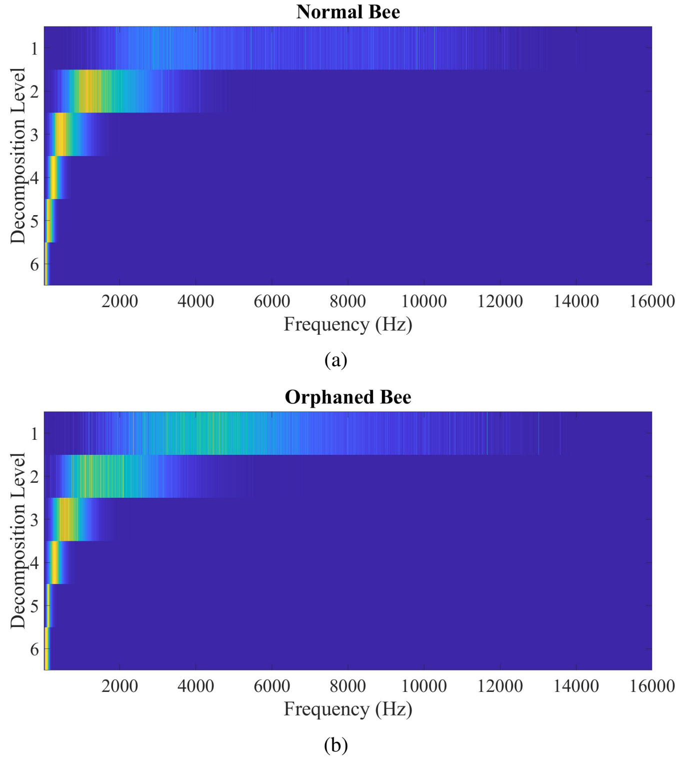


Fig. 5: Features extraction exploiting Hilbert-Huang transform in terms of decomposition level (i.e., intrinsic mode function) representing a different spectral content.

been acquired with an ADMP401 MEMS (micro-electro-mechanical sensor) microphones placed inside the colony, using a Raspberry-Pi equipped with a Behringer UCA222 sound card at 32 kHz. Frames of one minute have been used for the features extraction procedure.

B. Algorithms implementation

STFT and MFCCs features extraction approaches have been considered as reference. The analysis has been performed on MATLAB, exploiting its functionality. The HHT-based approach has been implemented following the procedure of Figure 1, selecting the first five intrinsic mode functions and then reordering each Hilbert spectrum. The wavelet-based approaches have been implemented considering Morlet mother wavelet for CWT and a ten level dyadic filter bank (as shown in Fig.2) for DWT.

C. Data Analysis

Fig. 3 shows the spectrograms obtained from the analyzed data. Comparing the normal situation with the orphaned bees some differences are visible especially in the higher frequency regions. In particular, some lines are evident in Fig. 3(a) that are not present in Fig. 3(b). Regarding the lower part of the spectrum, there is more energy in Fig. 3(b) than in Fig. 3(a) also in this case. These differences in the spectral content are more clearly visible in the MFCC coefficients of Fig. 4. In particular, focusing on the first five coefficients that are related to the lower frequencies, the first coefficient seems to have less energy in the orphaned colony, but the third, fourth and fifth coefficients seem to have more energy respect to the normal colony. The other coefficients have the same energy in both situations.

Fig. 5 shows the obtained results for HHT-based approach in terms of decomposition level and frequency range. Comparing the two situations, the harmonic content is different since the orphaned colony shows more harmonics at the higher and lower frequencies in contrast with the normal colony that has more energy in the middle frequencies, i.e., second level of IMF. With respect to other techniques, this approach gives a better estimation of the fundamental frequencies of the original signal. The shifting process used for empirical mode decomposition [19] removes riding waves and smoothes uneven amplitudes, leaving only the mode of oscillation contained in the original signal. In comparison with spectrogram, the HHT shows differences in the harmonic content with a better resolution, while with respect to MFCC, the HHT is more clear representing the harmonics actually included in the analyzed signal.

Fig. 6(a) shows the WT-analysis from a normal colony, while 6(b) shows scalograms from orphaned colony, and it is evident that we have obtained different spectral contents in the two situations. Orphaned colony figure shows a behaviour

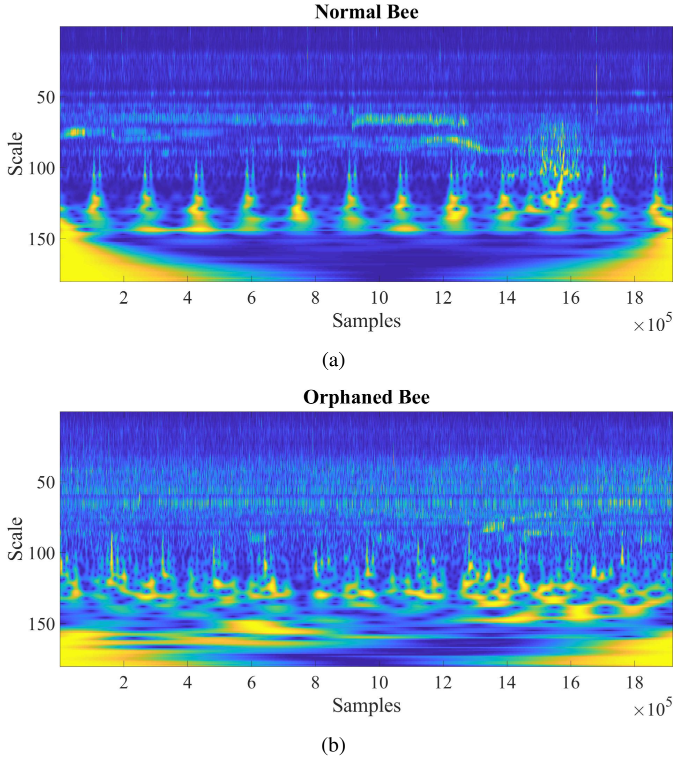


Fig. 6: Features extraction exploiting continuous wavelet transform with Morlet as mother wavelet.The number of scale values has been determined automatically in order to obtain a complete signal representation.

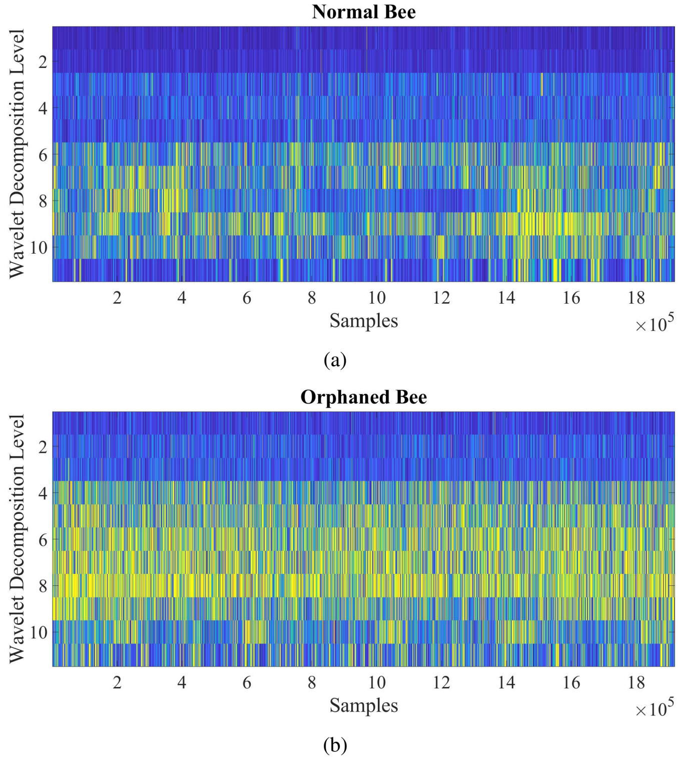


Fig. 7: Features extraction exploiting discrete wavelet transform with a 10-level dyadic filter bank. The 11st level corresponds to the approximation coefficient.

with more harmonics at lower frequencies, while at the higher frequencies the energy spread looks more uniform. On the contrary, the normal bee situation seems to have less and more defined frequencies. It should be noted that the highest energy region at the border of scales values must not be considered since is due to border effect, as also reported in the state of the art [26].

IV. Conclusions

The proposed work shows some innovative approaches for features extraction applied to honey bee sound classification problem. An HHT-based approach and WT-based approaches have been proposed for this task. Several experiments have been performed using STFT and MFCC as terms of comparisons, the HHT-based approach underlines well the different spectral content of two different sound situations and with respect to the algorithm proposed in [15] it could be used directly with neural networks and SVM algorithms. Finally the WT-based approaches show the best performance, allowing a clear distinction between the two situation, with the queen bee present and without queen bee. It is worth nothing that wavelet has already used for animal sound analysis but it has never been applied to honey bee sound. In this paper we have demonstrated that the WT properties could be very useful for this kind of signals. Finally, we must underline that wavelet transforms can be implemented as a filter bank reducing the algorithm computational cost and WT coefficients could be directly used for signal classification avoiding the computational cost of machine learning algorithm. Future works will be oriented to the use of the proposed approaches int automatic classification of different situations such as swarming, diseases, or other dangerous events.

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