Katydids Acoustic Classification on Verification Approach based on MFCC and HMM

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Abstract—**This work presents a new proposal towards the development of an intelligent system for automatic classification of katydids. Katydid is the common name of a certain large, singing, winged insects that belongs to the long-horned grasshopper family (*Tettigoniidae*) in the order of the *Opthoptera*. We propose a sound parameterization using Mel Frequency Cepstral Coefficients (MFCC) because these coefficients approximate the human auditory system's response more closely than linear-spaced frequencies. This proposal is based on the use of a HMM classifier to process the MFCCs. Our proposal is based on two approaches, identification and verification; and it has obtained 99.31% of accuracy in the identification stage and has increased to 99.97% of accuracy in the verification stage.**

Keywords: Mel Cepstrum Coefficients, Hidden Markov Models, Signal Processing, Sound Classification, Acoustic Monitoring, Katydids.

I. Introduction

Insects are the most diverse animal group, with over one million described species. Katydids in some cases are considered pests by commercial crop growers, and these insects are sprayed to limit its growth. Identification of species of insects is an important task in pest control and food biosecurity due to the pervasiveness of insects in our environment, as in other fields. On the other hand, katydids belong in the order of the *Opthoptera*, which its acoustic monitoring can be a potential key for conservation and evaluation of quality habitats [1].

As in others fields, automation is a common response of humankind to activities that should be repeated several times. Species identification is one of such activities, where the process of gathering information and analyzing it requires a repetitive process. Nevertheless, regardless the approach used, there are some issues associated with reliable species identification like quality training sets, errors in identification, scaling up the process up to differentiate among a large number of species and dealing with species that a system has not been trained to identify [2]. This is why species identification should be done carefully to reduce the impact of such issues in the process of classification.

A lot of progress has been made in the field of automated acoustic species classification, but not so much with specific species of insects as Katydids or other species. Besides most of the work done is centered in general insect sound recognition, we have found some related interesting research done in the past years. In [3], there's an outstanding approach where the authors achieves classification among various species of crickets, katydids and cicadas. This approach uses Linear Frequency Cepstral Coefficients as parameterization with Probabilistic Neural Networks (PNN), Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM), with the last two trained based on a standard version of the expectation-maximization algorithm, obtaining an identification accuracy of 98.7% on the levels of suborder and family, and 86.3% on the level of specific species out of 313 species from the North America collection (SINA).

Another interesting approach is found in [4], where an approach is presented to help in the recognition of insects for pest management. This approach is based on Sub-band Based Cepstral (SBC) parameters with HMM models and obtains a 90.98% of accuracy in a database of 50 different insect sounds samples of the North America collection (SINA). In [5], a bioacoustics signal recognition system is proposed to classify British *Opthoptera* (Katydids). It uses a pure time domain approach known as Time Domain Signal Coding (TDSC) coupled with an Artificial Neural Network (ANN) classifier, and it was successfully tested on 25 species of British *Orthoptera* with 99% recognition accuracy and 10 species of Japanese bird with 100% accuracy. In [6], a mathematical method is proposed to automatically detect acoustic activity of the red palm weevil, using Vector Quantization (VQ) and GMM. The algorithm of this work successfully achieved detection ratios as high as 98.9% with data collected from the laboratory at the Computer and Electronics Research Institute (CERI) at King Abdulaziz City for Science and Technology (KACST), as well as from the field in environmental conditions.

There is no doubt that significant progress has been made in the field of acoustic recognition in biology. However, more knowledge is needed combining different types of features in order to increase the number of species that systems are capable to recognize and classify with a high rate of success. Therefore, this present work introduces a novel intelligent system to successfully classify 26 different species of Costa Rican katydids from the family *Tettigoniidae*. Our approach is based on Mel

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Frequency Cepstral Coefficients (MFCC) using a Hidden Markov Model (HMM) classifier. The proposed system is based on audio signal processing techniques and decisions support systems, taking advantages of both to create a useful bioinformatics system to classify katydid's species. Moreover, this work introduces a MFCC parameterization using a verification approach, where the sounds are analyzed and classified by a HMM classifier. Two approaches have been used, identification for the first stage, and verification for the second stage. The first stage consists of a learning process where the system identifies and classifies katydid's species. Towards that classification, a verification process is done to confirm the correct recognition of Costa Rican katydid's species of the *Tettigoniidae* family, in comparison to previous work where identification was the core approach.

Our approach has given a 99.31% of success rate in the identification stage, but its success rate has increased to 99.97% thanks to the novelty use of a verification process in the recognition system. Our proposal is the first work in the area to use a verification stage. We consider that the verification stage we have added to the system makes it unique and accurate due to the reliability in species recognition. This stage allows the system to successfully recognize and classify species of Costa Rican katydids of the *Tettigoniidae* family in the database used. Compared to previous works, if a sound is not documented in the database, those systems tend to fail in the identification stage. Nevertheless, the incorporation of a verification process lets the system successfully indicate that the katydid sound does not belong to a trained class, letting biologist detect possible emergence of new species not yet documented. The remainder of this paper is organized as follows. How the sounds were preprocessed is being described in Section II. Section III describes the feature extraction process followed to obtaining the relevant information of katydid's chants in order to use this information as an input of the classifier. The HMM classification system used is described in Section IV, describing the two approaches followed, identification and verification. Then, Section V contains the experimental settings applied in this research; as are the database, the experiment methodology and the results obtained. Finally in Section VI, the conclusions of this work are shown.

II. Katydid's Sound Detection and Segmentation

Katydid's sounds are not uniform between species. For that reason, a simple but effective semi-automatic algorithm has been developed to successfully detect the katydid's chants and proceed to a segmentation process to extract the highest number of samples from a continuous recording of katydid's sounds. Towards the development of the proposed system, a set of continuous recordings of 26 species of Costa Rican *Tettigoniidae* has been obtained from [14].

In order to use those continuous recordings in our proposal, it was necessary to create a preprocessing stage to correctly detect the regions of activity for each katydid species. To accomplish this task, a procedure has been developed to be complemented with an algorithm proposed in [7] to detect sounds by its pitch and differentiate signal from silence. This algorithm tracks the pitch strength trace of a signal, determining clusters of pitched and unpitched sound, and the criterion used to determine these clusters is the local maximization of the distance between the centroids.

Our detection and segmentation process consists of taking each one of the 26 continuous recordings and applying a set of calculations towards the detection of chant's activity regions.

A. Sound Detection

A windowed discrete time Fourier transform (DTFT) is calculated based on the signal as shown in (1). This process allows transforming a time domain signal into the frequency domain. This transformation is done based on the sampling frequency and a class dependent window. Once the FFT is computed, a set of filtering techniques are applied to correctly detect chant activity regions. As can be seen in Figure 1a and 1b, our original signal is transformed into a frequency domain function represented by its spectrogram.

$$X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-i2\pi f t} \qquad (1)$$

Afterwards, a linear interpolation of $|X(f)|$ is computed based on a logarithmic space vector of 1000 points between 1000 and 10000, obtaining a $Y'(a,b)$ function. Next, we apply some processing as shown in (2) and (3). Finally, the algorithm proposed in [7] is applied to the signal $P(b)$, obtaining a binary signal. This output signal has a value of one where chant activity is present and has a value of zero otherwise, as shown in Figure 1c. The algorithm determines the clusters at every instant of time T by assigning the samples in the neighborhood of T to the classes, using as optimization criteria the

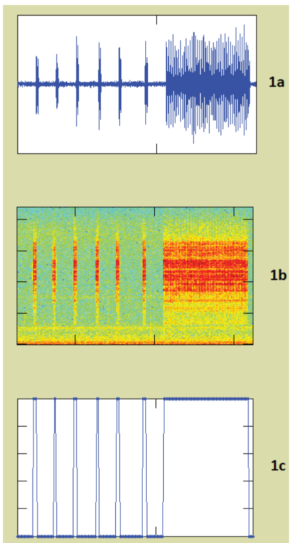

Figure 1. a) Fragment of the original sound signal, b) Frequency domain signal (spectrogram) and c) Preprocessed signal

maximization of the distance between the centroids. The analysis is performed at different scales by using window sizes that increase by a factor of $\sqrt{2}$.

$$Z(a,b) = \sqrt{Y'(a,b)} \quad (2)$$

$$P(b) = \sum_a Z(a,b) \quad (3)$$

Once the detection process has successfully found the chant's activity region, a manual lookup is performed; this way an adequate window size is found for every single class. This window sizes are stored for further processing in the segmentation stage.

B. Segmentation

The segmentation stage consists of taking a continuous recording of a species and obtaining the highest number of samples of that species. To achieve this task, a cross-correlation is performed on each of the recordings. Cross-correlation is a measure of similarity between two waveforms as a function of the time-lag between them. With this technique, it is possible to find patterns of sound activity in the recordings. Once a pattern is found, the next step consists of cutting the recording into individual pieces, making these pieces individual samples to populate the database to be used in the learning process described further in these work.

The recording is divided in two waveforms to compute a cross-correlation on each segment of the signal. The length of both waveforms is modified during the segmentation process until a pattern is found. Once the pattern is found, the cutting is performed. The cross-correlations process is computed as shown in (4), where f^* denotes the complex conjugate of the waveform f. This process is done with all 26 species to obtain the corresponding pattern of each species and successfully cut the continuous recording into individual samples.

$$(f \star g)_i \overset{\text{def}}{=} \int_{-\infty}^{\infty} f^*(\tau) g(t+\tau)\, d\tau \quad (4)$$

III. Feature Extraction

In order to make a good classification system, we propose the use of MFCC as parameterization for the HMM. The MFCCs are passed to the HMM as feature vectors to allow the classifier to achieve pattern recognition between the coefficients.

To calculate the MFCC, we have followed the European standard algorithm documented by the European Telecommunications Standards Institute (ETSI) during 2003 under reference RES/STQ-00044. Based on this standard, an implementation of the MFCC extraction process is presented below.

The MFCC is derived from a nonlinear cepstral representation of sound. The difference between cepstrum coefficients and MFCC is that the latter coefficients are equally spaced on the mel scale, which approximates the human auditory system's response more closely than linear-spaced frequencies. The MFCCs used in this proposal are calculated following the steps shown in the next subsections.

A. Offset compensation

The offset compensation is done before the framing, removing the direct current component of the waveform signal offset. This compensation is done according to (5), where s_{of} stands for the offset-free input signal and s_{in} stands for the input signal.

$$s_{of}(n) = s_{in}(n) - s_{in}(n-1) + 0{,}9999 \times s_{of}(n-1) \quad (5)$$

B. Framing

After obtaining an offset free input signal, the signal is divided into overlapping frames of N samples with M number of frames per unit time. The specific values of N and M depend on the sampling rate of the signal. In our case, the sampling rate in Katydid sounds is 44.1 kHz. For this proposal, the value of N has been established in 100 samples per frame. The value of M depends on the length of each chant.

C. Pre-emphasis

A pre-emphasis filter is applied to the offset-free input signal, as shown in (6), where s_{pe} is the signal after the pre-emphasis operation. This filtering is done to emphasize the high frequencies of katydid's sounds, which are generated by katydid's legs.

$$s_{pe}(n) = s_{of}(n) - 0{,}97 \times s_{of}(n-1) \quad (6)$$

D. Windowing

After the pre-emphasis, the signal is windowed according to the framing values obtained in the framing stage, calculating a Hamming window of length N to the signal. This windowing is performed shown in (7), where s_w is the result of windowing.

$$s_w(n) = \left\{0{,}54 - 0{,}46 \times \cos\left(\frac{2\pi(n-1)}{N-1}\right)\right\} \times s_{pe}(n), \ \ 1 \le n \le N \quad (7)$$

E. FFT

After the windowing, the Fast Fourier Transform (FFT) is computed for each frame of N samples, obtaining the discrete Fourier transform (DFT) and its inverse. The process mentioned is done via (8), where $s_w(n)$ is the input to the FFT block, $FFTL$ is the block length, and bin_k is the absolute value of the resulting complex vector.

$$bin_k = \left| \sum_{n=0}^{FFTL-1} s_w(n) e^{-jnk\frac{2\pi}{FFTL}} \right|, \ \ k = 0, \dots, FFTL-1 \quad (8)$$

F. Mel Filtering

After computing the FFT, a set of triangular filter banks is used to approximate the frequency resolution of the human ear. The mel frequency scale is linear up to 1000 Hz and logarithmic thereafter. A set of overlapping Mel filters are made such that their center frequencies are equidistant on the mel scale. This mel filtering is done via (9a), (9b), (9c) and (9d) where $cbin_i$ stands for the center frequency of the *i-th* Mel channel in terms of FFT bin indices, f_{ci} is the center frequency of the *i-th* Mel channel and f_s is the signal sampling rate.

$$Mel\{x\} = 2595 \times \log_{10}\left(1 + \frac{x}{700}\right) \quad (9a)$$

$$f_{c_i} = Mel^{-1}\left\{Mel\{f_{start}\} + \frac{Mel\{f_s/2\} - Mel\{f_{start}\}}{23+1} i\right\}, \quad i = 1, \ldots, 23 \tag{9b}$$

$$cbin_i = round\left\{\frac{f_{c_i}}{f_s} FFTL\right\} \tag{9c}$$

$$fbank_k = \sum_{i=cbin_{k-1}}^{cbin_k} \frac{i - cbin_{k-1} + 1}{cbin_k - cbin_{k-1} + 1} bin_i + \sum_{i=cbin_k+1}^{cbin_{k+1}} \left(1 - \frac{i - cbin_k}{cbin_{k+1} - cbin_k + 1}\right) bin_i \tag{9d}$$

G. Cepstral Coefficients

Finally, the cepstral coefficients are computed from the output of a non-linear transformation block as shown in (11), where *coeff* stands for the number of Mel Frequency Coefficients desired to calculate. The non-linear transformation is calculated as a logarithm function of the filter bank output, as shown in (10).

$$f_i = \ln\left(fbank_i\right), \quad i = 1, \ldots, 40 \tag{10}$$

$$C_i = \sum_{j=1}^{40} f_j \cos\left(\frac{\pi \times i}{40}(j - 0{,}5)\right), 0 \le i \le coeff \tag{11}$$

IV. CLASSIFICATION SYSTEM

The proposed classification system is based on the HMMs. An HMM is a string of states $\boldsymbol{q}$, jointed with a stochastic process which takes values in an alphabet S which depends on $\boldsymbol{q}$. These systems evolves in time passing randomly from one state to another and issuing in each moment a random symbol of the S alphabet.

When the system is in the state $\boldsymbol{q_{t-1} = i}$, it has a probability $\boldsymbol{a_{ij}}$ of moving to the state $\boldsymbol{q_t = j}$ in the next instant of time and the probability $\boldsymbol{b_j(k)}$ of issuing the symbol $\boldsymbol{o_t = vk}$ in time $\boldsymbol{t}$. Only the symbols issued by the state $\boldsymbol{q}$ are observable, nor the route or the sequence of states $\boldsymbol{q}$. That's why the HMM obtain the appellative "hidden", since the Markov process is not observable.

In this proposal, we have worked with a Bakis HMM also called *left to right*, which is particularly appropriate for sequences. The Bakis HMM is especially appropriate for sequential sound data because the transitions between states are produced in a single direction. Therefore, it always advances during the transitions of its states, providing the ability to keep a certain order in this type of models with respect to the observations produced where the temporary distance among the most representative changes. Finally, the HMM model used has been configured with a range from 2 to 170 states and 32 symbols per state.

A. Identification Approach

For identification purposes, we used an HMM model with 26 feature vectors that corresponds to each of the Katydid's classes to be identified. The training was done using on average 10 katydid's sounds per species and creating the 26 feature vectors with sounds coming from different species. This training was done with the training function to which it sends as a parameter the observation information obtained in the feature extraction process. This function defines a state transition matrix and an initial observation symbols matrix. The number of iterations in the HMM was 1160, using the sound samples generated thanks to the segmentation process described in Section II.

The behavior of the HMM classifier consists in comparing the input feature information vector corresponding to a determined class, with a set of pattern features vector. At least, there should be one pattern feature vector for each of the classes. The feature vectors of each class are introduced to a single HMM. For example; in class 1 there should be an input of the feature vectors corresponding to individual 1, in class 2 there should be an input of the feature vectors corresponding to individual 2, and so on. This way, a single HMM that contains the information of all the individuals is generated.

Once the HMM is ready, the test mode can be pursued. In this mode, the system receives as input a feature vector and the system compares it with model generated in the learning stage. This comparison takes the maximum of the HMM with the output and the identified class. If the output exceeds this maximum, the input feature vector belongs to an individual in the database; otherwise the input feature vector belongs to an individual outside of the database

B. Verification Approach

In this approach, the HMM classifier is treated as a bi-class classifier, generating 26 models (one for each species), thus in the testing phase the system indicates if sounds belong or not to a trained class. This means that there should be created as many models as there are classes, being each model composed by the feature vector of a class to which it is considered as positive and all the remaining feature vectors to which there are considered as negative. In the test mode of the verification process, the sound to be classified is preprocessed according to the method described in Section II, and then the MFCC of this sound are extracted according to the process described in Section III. If the output exceeds a determined threshold, the katydid's sound to be verified would be verified as from the class to which the individual is said to belong. Otherwise, the individual is rejected. The threshold obtaining process is based on the false rejection rate and the false acceptance rate. This way, if a sound is not documented in the database; those systems tend to fail in the identification stage as in [3-6] and [9]. Nevertheless, the incorporation of a verification process let the system successfully indicate that the sound does not belong to a trained class.

V. EXPERIMENTAL SETTINGS

In order to implement the classification system based on an HMM classifier, a set of experimental settings has been configured. These settings includes the database used in all the experiment's scenarios, the methodology followed to achieve a good classification result, and the analysis of the results obtained.

A. Database

The database used was obtained directly from [14]. This database contains a total of 243 katydid's chants corresponding to 26 genders and species from 12 different genus of *Tettigoniidae* from Costa Rica.

B. Experimental Methodology

The experimental methodology was structured using a supervised classification technique consisting in the use of a set of pre-established knowledge to determine the best classification scenario. Moreover, this experiment was divided in two stages. The first stage describes the HMM-based learning process whereas the principal objective is to obtain the best model, which is the one capable of classifying the sounds of the Katydids species. The second stage consists of a verification process of katydids sounds where the models created in the learning stage are used as input for verification. In the verification, the experimentation consists of validating if a species is from the class to which the individual is said to belong. In other words, verification is a *one-against-the-rest* validation process. The complete methodology followed can be seen in the flow diagram presented below in Figure 2, showing the general steps our proposal follows.

C. Results

In this section, it is presented a set of different tests made with all the feature vectors and the classifier. Showing both the results of the identification process and the results of the verification process; providing an approach of which configurations of the classifiers offer a better Total Success Rate (TSR). Once all the results are obtained, it can be verified that our katydid's sounds classification system can identify and verify the individuals in a database, offering an acceptable success

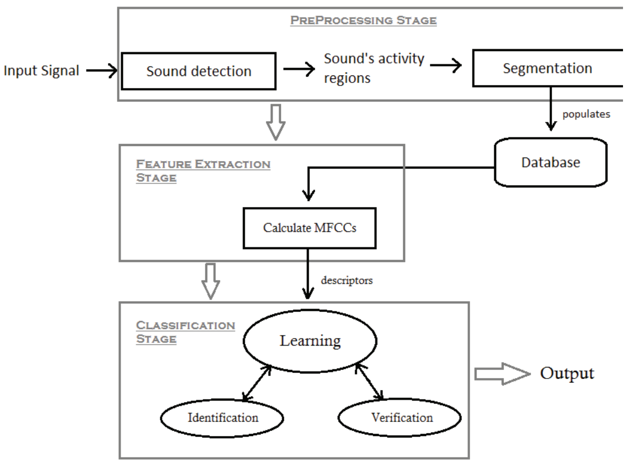

Figure 2. Methodology of proposed system

rate. The tests performed were made with a database of 26 classes with an approximate of 10 samples of each class, though there were classes with fewer samples. In the tests made with the classifier we used 3 different scenarios. We have taken 40%, 50% and 60% of samples for training purposes, and the remaining samples for test purposes. The results of the tests are presented in tables were the column TSR shows the success rate in terms of mean and variance.

The experiments performed and its results obtained with each of the feature vectors calculated in the feature extraction process for the identification system using HMM are exposed in this section. Experiments have been based on two approaches; the first one is based on identification and the latter one on verification.

1) Identification Approach

The tests performed for the identification process were repeated a total of 20 times for each configuration of HMM states for a total of 1160 experimentations. The tests were performed for different number of MFCCs, looking for the best combination of MFCC and HMM states. The number of coefficients selected for the tests were 13, 18 and 24 coefficients, based on previous research [10-13], showing that usage of MFCCs with this range of coefficients obtains a good parameterization of sound. The states of the HMM were varied in a range of 2 to 170 states. This variation on the number of states of the HMM and the number of coefficients selected has been used to create a high number of test scenarios, indicating that overpassing those boundaries, the results tends to decrease considerably, making these values a good set to reach variation in the results during experimentation of the proposed system.

According to our experiments, it has been found that the best results are obtained when selecting a number of states similar or equal to a multiple of the number of MFCCs; that is, if 13 Mel coefficients are used as parameterization of the sound, the number of states of the Bakis HMM classifier should be 13, 26, 39 or any other multiple of 13. A table showing the best results in identification is shown in Table I.

2) Verification Approach

The test performed for the verification process were also repeated a total of 20 times for each species of Costa Rican *Tettigoniidae*. Each configuration has a total of 200 experiments, and due to the 26 species the system is classifying, a total of 5200 experimentation were done in

TABLE I.
IDENTIFICATION RESULTS DUE TO EXPERIMENTATION

No. Coefficients	No. HMM States	TSR[1] Mean % ± Std
13	13	99.31 ± 1.21
13	26	99.14 ± 0.93
18	18	99.18 ± 1.20
18	36	99.01 ± 1.32
24	6	99.05 ± 0.92
24	12	99.31 ± 0.91
24	24	99.09 ± 0.65

[1] TSR stands for Total Success Rate

TABLE II.
VERIFICATION RESULTS DUE TO EXPERIMENTATION

No. Coefficients	No. HMM States	[2]Accuracy % ± Std
13	13	99.86 ± 0.32
13	26	99.79 ± 1.23
18	18	99.18 ± 1.20
18	36	99.35 ± 1.84
24	6	99.65 ± 1.63
24	12	99.97 ± 0.81
24	24	99.19 ± 1.65

[2] Accuracy calculated as a cumulative accuracy of all species verification within the same configuration of coefficients and HMM states

the verification stage. The experiments for the verification process were performed only with the method were the best result has been obtained. Thanks to the identification system, the best result scenarios that have been obtained for the verification stage are the ones shown in Table II. While in the first stage it was created just a single model with all the 26 classes in it, in the second stage it is created a model for each one of the classes which corresponds to each one of the species being classified.

VI. DISCUSSION AND CONCLUSIONS

This work has introduced a classification system through the Mel Frequency Cepstral Coefficients of chants of katydid's species, being capable of performing the recognition and verification of katydid's sounds.

The success rates in identification were around 99.31% with a variance of 0.91; improving this results in the verification process to a reliability of 99.97% working with our database of 26 different species of Costa Rican katydids. Thanks to all experimentations scenarios, it has been discovered that best results are obtained selecting a number of states similar or equal to a multiple of the number of Mel frequency cepstral coefficients, letting the system to correctly identify and validate the different species of *Tettigoniidae* from Costa Rica. It is important to mention that this classification method gives a better result rate than the methods presented previously in [1], [3], [4], [5] and [6], due to the proximity to a 100% classification and the novel incorporation of verification stage during classifications. Moreover, this paper has contributed with a taxonomical quantitative model, showing that katydid's acoustic classification system can simplify the features in the moment of its classification, obtaining a sufficient discriminatory result.

More work should be done in species automatic classification systems, allowing us to obtain more knowledge in combining different types of features in order to increase the number of species that systems are capable to recognize and classify with a high rate of success. A future approach would be to successfully detect, recognize and classify multiple species from different subfamilies of *Tettigoniidae* in controlled environment recordings as well as in recording taken directly from the field, proving the sturdiness of our algorithms. These tests would be made with different databases of katydid's chants around the globe demonstrating the effectiveness of our proposal.

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