Recognition of bird species based on spike model using bird dataset

Ricky Mohanty a, *, Bandi Kumar Mallik b, Sandeep Singh Solanki a

a Birla Institute of Technology, Mesra, Ranchi, India
b Central Poultry Development Organisation (Eastern Region), Bhubaneswar, India

ABSTRACT

Birds have often been recognised as the first informants of climatic change in our environment. Bird species recognition has assumed great significance not just for checking the survival of birds but also as an early warning signal of the declining health of earth and its climate. Earlier researchers have established recognition of bird species based on sounds from repository available online which were region-specific. In this article, we have presented the spike-based bird species recognition model, which deals with the process of identifying the bird species based on their vocalization or call. The dataset comprises of 14 bird species vocalizations. These recordings have been taken in their natural environment. The calls were recorded using a digital recorder and a unidirectional microphone at Central Poultry Development Organization (CPDO), Eastern Region, Bhubaneswar, India. The interpretation of this data provided in this article is associated with the research article titled "Automatic Bird Species Recognition System using Neural Network based on Spike" [1].

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The dataset in this article described in Table 1 shows the call data collected of 14 bird species from Central Poultry Development Organization, Bhubaneswar, India. In figure one, the spectrogram depicts shapes (curves) and pattern (syllable) of the birds (Japanese Quail, Guinea Fowl, Rhode Island Red and Aseel Brown). Fig. 2 illustrates the segmentation of bird sound into a series of syllables. One or more elements together make a syllable, and a set of syllables produce a phrase well explained in Fig. 2. Fig. 3 represents the filtering of Japanese quail sound.
2. Experimental design, materials, and methods

The automatic bird species recognition system has been designed to keep a check on a particular bird, its number, and the survival of rare species. The database collection of all species has been done

| SL. No. | Common name            | No. of birds | Calls |
|--------|------------------------|--------------|-------|
| 1      | Barred Plymouth Rock   | 9            | 50    |
| 2      | White Plymouth Rock    | 11           | 39    |
| 3      | Red Codish             | 8            | 40    |
| 4      | Black Rock             | 7            | 28    |
| 5      | Naked Neck             | 8            | 50    |
| 6      | Rhode Island Red       | 9            | 46    |
| 7      | Kalinga Brown          | 14           | 38    |
| 8      | Japanese Quail         | 8            | 77    |
| 9      | Guinea Fowl            | 10           | 41    |
| 10     | Whiteleg Horn          | 9            | 36    |
| 11     | AW Cross               | 5            | 27    |
| 12     | Aseel Brown            | 15           | 60    |
| 13     | Colour Cross           | 12           | 43    |
| 14     | Vanaraja               | 8            | 65    |
| total  |                        | 133          | 638   |

Fig. 1. a) Spectrogram of the Japanese Quail bird sound. b) Spectrogram of the Aseel Brown bird sound. c) Spectrogram of the Guinea Fowl bird sound. d) Spectrogram of the Rhode Island Red bird sound.
Fig. 2. Shows the seven syllables of the Japanese Quail Bird Sound.

Fig. 3. Represent the unfiltered and filtered sound of Japanese Quail.
using a recorder and a microphone mentioned in Table 1. These data are useful to understand the pattern of these birds, and healthy birds showed no prominent symptom of infectious disease. This data can help to investigate disease recognition for birds affected by bronchitis or respiratory infections in the future. The process started with the removal of noise as the frequency and temporal trajectories of bird sound and noise overlap. For removal of noise, a discrete wavelet transform was used as in Fig. 3.

Fig. 1(a–d) represents a pattern in the spectrogram of different bird species like Japanese Quail, Aseel Brown, Guinea Fowl, and Rhode Island Red. This pattern was used for identifying bird species as in [5–7]. The various works done earlier used this type of pattern of manual matching of template of the bird specific species but were less accurate in Refs. [3,4]. The shapes referred to as elements of a bird’s sound.

Bird’s vocalization or bird’s sound split into bird call (simple and shorter sounds uttered by both sexes) and bird song (long and complicated sounds mainly uttered by male bird). The smallest part of all these birds’ vocalizations is the element. So segmentation was done based on the syllable. The information contained in the syllable represents the feature vector.

For the simulation, the experiments were implemented in Matlab 2015b software. The test platform was Intel core 3i 8th generation, 2.2 GHz CPU, 4 GB RAM with Windows 10 operating system. Before the preprocessing of the raw bird sound, one-minute recording of birds was divided into 12 equal frames of 5 Sec frames by using the removal of silence Matlab code as provided in the supplementary section in Ref. [1]. Removal of noise from frames takes place using discrete wavelet transform. For the segmentation of frames, Short Time Fourier Transforms was used for obtaining spectrograms. Syllables were extracted from this spectrogram based on the energy as in Ref. [2] using syllable segmentation Matlab code as provided in the supplementary section [1]. Syllables were used for feature extraction, and then the standardization process of features takes place. This standardization was followed by the classification and recognition of bird species using the Spiking Neural Network with the Permutation Pair Frequency Matrix Matlab code as provided in Ref. [1].

Acknowledgments

The authors thank Dr. Indira Nayak and Dr. Akash Katiyar for their help with data collection of raw bird sound and preparing for further process.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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