An Artificial Intelligence Recognition Algorithm for Yangtze Finless Porpoise

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***Abstract*—Processing marine-mammal signals for species classification and monitoring of endangered marine mammals are problems that have recently attracted attention in the scientific literature. Currently, the detection of signals of interest is typically accomplished through a combination of visual inspection of spectrograms and listening to the data. This paper presented an automatic identification algorithm for the Yangtze finless porpoise based on Hilbert Huang Transform and BP artificial neural network. The algorithm includes three steps: signal preprocessing, feature extraction and signal identification. In feature extraction stage of the algorithm, the algorithm extracts a 11-Dimension signal feature vector based on Hilbert Huang transform, Shannon entropy and Fourier transform. In the identification stage, the BP artificial neural network is trained by using the feature vector as input. At last, some experimental acoustic data files of finless porpoise are used to test the validity of the automatic identification algorithm. The identification rate of the algorithm proposed in this paper reaches 90% with highest false positive rate (<92 per hour) according to the human observation on the time-frequency spectrum. Because the Yangtze finless porpoise is one of the most critically endangered mammals in the world, so the presented method has great practical significance for protecting and monitoring the Yangtze finless porpoise in the wild.**

***Index Terms*—Finless Porpoise, Hilbert Huang Transform, Shannon Entropy, BP artificial neural network.**

I. INTRODUCTION

In recent years, passive acoustic monitoring has proven to be one of the most effective methods for monitoring the presence and movement of marine mammals due to the fact that cetaceans are difficult to locate visually from the surface, but acoustic visible. The Yangtze finless porpoise is endemic to the middle and lower reaches of the Yangtze River and its two adjoining lakes, China. It is the only freshwater cetacean remaining in the Yangtze River following the presumed extinction of the baiji [1]. The threats to Finless porpoise include a collection of illegal fishing(electro-fishing and gillnets), pollution, transportation and water constructions. The population size has been declining, and the distribution ranges have been reduced sharply in the past thirty years [2]. Proper survey and management of their populations has therefore become necessary. In recent years, several Yangtze finless porpoise research surveys have been organized by the Chinese government. Traditional visual-based observation surveys are very tedious, labor intensive, have limited accuracy, and strongly depend on the weather condition. The finless porpoises produce echolocation click trains that make them acoustically visible day and night. Acoustic-based survey methods are expected to be indispensable for surveying finless porpoises who spend most of their time underwater [3]. So researchers began to use passive acoustic methods to study the finless porpoise in recent years.

Satoko Kimura from National Research Institute of Fisheries Engineering, Japan, has used A-tag from a moving platform to estimate the density and abundance of the finless porpoises [4]. Kexiong Wang from Institute of Hydrobiology, the Chinese Academy of Sciences, China, has used fixed-location acoustic arrays concurrent with visual observations to determine the detection capabilities of the acoustic system. The system can detect the presence of porpoises with a correct detection of 77.6% [5]. Songhai Li from Institute of Hydrobiology, China, has used A-tag to density of the porpoise in Yangtze river by fixed and mobile platform [6]. Results show these methods can detect the presence of finless porpoises. But A-tag only records the amplitude of the signal which is easy to cause error detections.

With improving, more accessible and cheaper ocean technology, a large amount of data that can be collected and thus needs to be analyzed is increasing rapidly. Significant research has been done on the design and construction for automated detection of marine mammals. This paper proposed an automatic finless porpoise identification algorithm based on Hilbert Huang transform, Shannon Entropy and BP artificial neural network. This algorithm has a much higher assignment rate and can be used for monitoring of finless porpoise in the wild.

II. DATA COLLECTION

For the development and testing of the artificial intelligence algorithm, 6 days of underwater recordings from the Tongling River Dolphin National Reserve were used. In February 2006, the state council general office approved the Tongling River Dolphin Reserve promote to national nature reserve. There are about ten porpoises living in this reserve at present. So some finless porpoise passive acoustic experiments were conducted to research the echolocation of Yangtze finless porpoises in Tongling River Dolphin National Natural Reserve in Tongling (30.46 –30.05 N, 117.39 –117.55 E), Anhui Province, China. These recordings were taken for a long time.

Fig. 1. The Yangtze finless porpoise.

The finless porpoise acoustic signals were recorded by an underwater acoustic signal acquisition system. The hydrophone is ResonTC-4013 which is a broadband hydrophone with usable frequency from 1Hz to 170kHz and the acquisition equipment is NI PXle-1071. The whole underwater acoustic recording system is able to record acoustic signals up to 200 kHz. The highest frequency of finless porpoise can achieve nearly 160 kHz. So this system should be sufficient to receive and store the sound signals produced by the finless porpoise.

III. Methods and Results

This section describes the artificial intelligence identification algorithm in detail, then the experimental data was used to examine the effectiveness of the algorithm. The algorithm is divided into three steps: signal preprocessing, extraction feature and identification. The basic recognition architecture for the algorithm is shown in Fig.2.

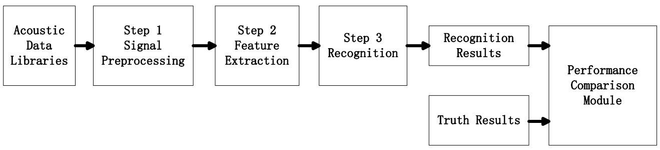

Fig. 2. Architecture of the system used to test the algorithm

Sounds from the library are processed through step1-3 and result in recognition results, whereby its performance is evaluated by comparison with a truth result (generated by human observers).

A-C will introduce some signal processing method for finless porpoise signal. D-G will show the algorithm and the results in detail.

A. Characteristics in Frequency Domain

As shown in Fig.3, the waveforms of finless porpoise signals have variable shapes. But these signals spans in the similar frequency range. Fig.4 shows the distribution in frequency domain of one finless porpoise signal. Although, the waveforms are totaly different in the time domain, they have the similar frequency distribution. So we choose the peak frequency f_p and 3 dB bandwidth w_{3dB} as features for the finless porpoise signal.

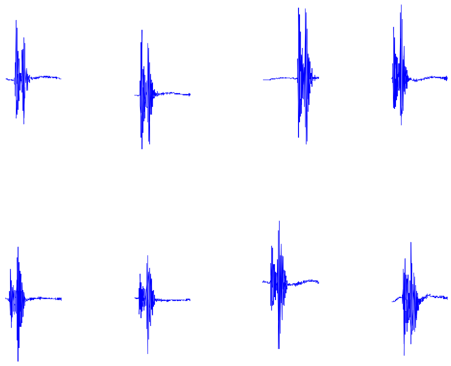

Fig. 3. Some different waveforms of porpoise signal

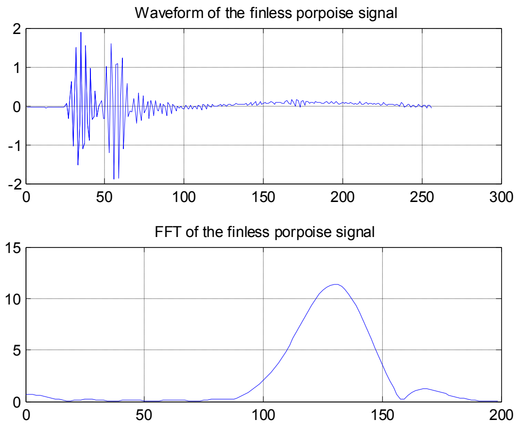

Fig. 4. The waveform and FT of a porpoise signal

B. Hilbert Huang Transform and Hilbert Marginal Spectrum

Hilbert-Huang Transformation (HHT) is a new time-frequency method to decompose the signal into a physical meaning instantaneous signal based on instantaneous frequency. The method of HHT was first designed by Norden E Huang in 1998 making creative improvement for Fourier transform. It is a kind of method that can be applied to nonlinearity, non-stationary signal processing. Hilbert-Huang transform method consists of Empirical Mode Decomposition (EMD) and Hilbert transform (HT). The EMD decomposition process:

(1) Finding out all the local maximum points and minimum points of the signal $x(t)$, fitting it as upper and lower envelope curve of the original data sequence, the average value of upper and lower envelope curve is the average envelope curve m_1, the original data sequence minus m_1, which can get a new data

sequence h_1 with removing the low frequency. The data sequence h_1 is not stable, so repeating the above process at n times in order to make the value of average envelope curve tend to zero, and at this time, h_{1n} is the first Intrinsic Mode Function (IMF) (c_1) which represents the highest frequency component in the signal data.

(2) $x(t)$ minus c_1, which can get a new data sequence without the high frequency components, repeating process (1) can get a new sequence of c_n and the undecomposable sequence of r_n which represents the average value or trend value. So the original sequence $x(t)$ can be considered as the sum of IMF component and a residual.

$$x(t)=\sum_{i=1}^{n}c_i+r_n \tag{1}$$

After decomposed, signals get many combinations of IMF, Hilbert transforming each IMF component so that instantaneous frequency of each IMF component is given. Integrating all the components of the instantaneous spectrum to get the Hilbert spectrum. Transforming each IMF after getting IMF component , setting it to $y(t)$:

$$y(t)=\frac{1}{\pi}\int\frac{x(\tau)}{t-\tau}d\tau \tag{2}$$

A combination of $x(t)$ and $y(t)$ is the analysis signal $z(t)$ which is shown with polar coordinates:

$$z(t)=x(t)+j*y(t) \tag{3}$$

Furthermore:

$$a(t)=\sqrt{x^2(t)+y^2(t)}$$
$$\theta(t)=\arctan(\frac{y(t)}{x(t)}) \tag{4}$$

Definition of instantaneous frequency:

$$w(t)=\frac{d\theta(t)}{dt} \tag{5}$$

$w(t)$ is the single value function of time through (5), that is to say, a certain time corresponds with relevant frequency, each IMF and calculating amplitude spectrum of relevant analytic function and instantaneous frequency, thus the original signal can be expressed as follow:

$$x(t)=\mathrm{Re}(\sum_{i=1}^{n}a_i(t)\exp(j\int w_i(t)dt)) \tag{6}$$

Based on the Hilbert spectrum $H(w,t)$, through the integral of time, the Hilbert marginal spectrum can be defined as (7):

$$h(w)=\int_0^T H(w,t)dt \tag{7}$$

The Hilbert marginal spectrum shows each frequency range, which represent all accumulative amplitude in statistics.

Instantaneous amplitude and instantaneous frequency can be obtained after doing Hilbert transform to every IMF component. Frequency $w_i(t)$ and amplitude $a_i(t)$ is a function of time, which can constitute a time-frequency graph of three-dimensional that consists of amplitude, frequency and time. This graph is called Hilbert amplitude spectrum $H(w,t)$ [7]. Because Hilbert Huang Transform has clear physical meaning. As shown in Fig.5, the frequency changing process of the finless porpoise signal can be seen clearly.

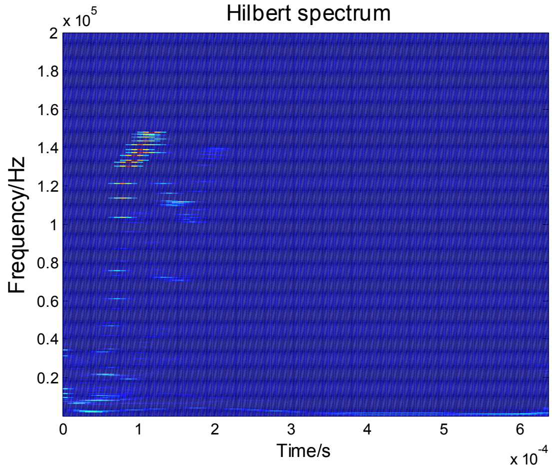

Fig. 5. The Hilbert spectrum of finless porpoise signal

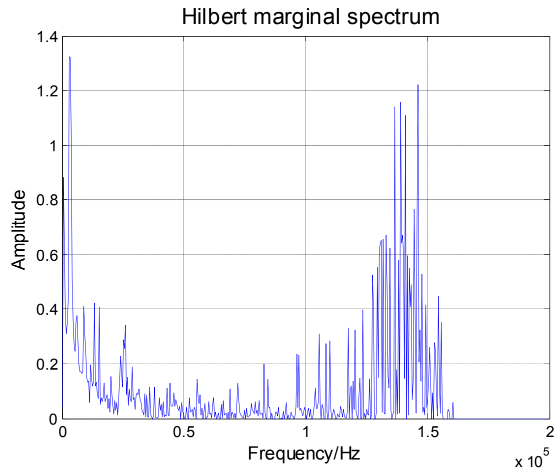

Fig. 6. The Hilbert marginal spectrum of finless porpoise signal

C. HHT marginal spectrum entropy

Information (Shannon) entropy measures the amount of information in a signal which represents the uncertainty of the signal. The greater Shannon entropy represents that the signal has more information and greater uncertainty. At discrete frequency point $f(k\triangle f)$, (7) gives the definition of the Hilbert Huang Transform spectrum entropy. k is the number of discrete points in the analysis frequency band.

According to the definition of the Shannon entropy, (8) is the definition Hilbert Huang Transform marginal spectrum entropy.

$$HHE=-\sum_{k=1}^{n}p_k\ln(p_k) \tag{8}$$

Where $p_k=h(k)/\ \Sigma\ h(k)$, which is the k th frequency corresponding to the probability of the amplitude. Then the value of the entropy will be normalized to 0-1. The normalization equation is $HHE=HHE/lnN$, where N is the length of sequence $h(k)$. As the Hilbert Huang Transform marginal spectrum entropy has perfect recognition ability for different complexity signals, it will be selected as a feature for identifying finless porpoise signal [8].

D. Signal Preprocessing

Step 1 incorporates signal segmentation and signal filtering. The goal of this step is to identify areas of high energy. A wide range of segmentation approaches exist. Signal of interest have energy between 70 kHz-160 kHz. Noise conditions can change dramatically throughout the course of the monitoring period. Filtering the original signal is a good way to remove the low frequency noise. The filtered signal segmentation will be used to extract the feature vector.

E. Feature Extraction

The algorithm will extract a 11-D signal feature vector based on Hilbert marginal spectrum, Fourier transform and Shannon Entropy. In the identification step, the finless porpoise signals can be detected by the trained BP artificial neural network using the extracted feature vector as input. Detailed descriptions are as follows:

As shown in the Fig.5, there are strong interference noise below 40kHz. In the Hilbert spectrum of finless porpoise signal, the frequency band ranges from 20 kHz to 160 kHz, mainly concentrated in the 100 kHz to 160 kHz. The Hilbert marginal spectrum ranging from 40 kHz to 160 kHz is divided into eight frequency band equally. Every frequency bandwidth is 20 kHz. The energy of every frequency band $E_{i,}i=1,2,\ldots 8$ would be calculated. The total energy is $E=\Sigma E_i$. Normalized energy of every frequency band is $e_i=E_i/E,\ i=1,2,\ldots 8$. The normalized energy sequence [e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8] will be defined as an eight dimensional feature vector which is extracted from Hilbert marginal spectrum. Peak frequency f_p, 3-dB bandwidth w_{3dB}, 8-D Hilbert marginal spectrum feature vector and Hilbert marginal spectrum entropy constitute a 11-D feature vector $F=[e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8, f_p, w_{3dB}, HHE]$. The 11-D feature vector F is defined as the recognition feature of the finless porpoise sounds.

F. The BP Artificial Neural Network Identification

The artificial neural network is an application of a mathematical model of information processing which is similar to the structure of the brain synaptic connections. It is the abstraction, simplification and simulation of the human brain, reflecting the basic characteristics of the human brain. Neural network is also a computational model, consisted by the weighted connections between the large numbers of neurons and each other. Each neuron represents a specific activation function, and the connection between two neurons represents a weighted value of the connection signal, which is equivalent to the memory of the neural network. The output of the neural network connected to the network, the weight values and excitation functions.

BP neural network usually consists of the input layer, output layer and hidden layer. According to Kplmogorov theorem, only one hidden layer of three-layer BP network can achieve the approximation of arbitrary functions. Each layer consists of a number of nodes, each node represents a neuron. There are connections between the upper nodes and lower nodes, with no contacts between the same layer of nodes. As a BP neural model structure of R input, each input has been given certain weights, which form the input of the neuron transfer function through sum with deviation [9].

A standard back propagation artificial neural network is used in the analysis. Deciding on the best architecture is a difficult problem in neural network technology. Regularization implies that many different configurations exist that vary in complexity, where each provide an acceptalbe performance level. When the neural network model structure is determined, it is time to learn and train. Trainng the neural network organizes a series of random weigths to achieve a minimum error condition. However, one could train the neural network using identical architectures, but resulting in different weight tables that meet similar error conditions. Furthermore, optimization could be done on the configuration of the architecture. In prior work, optimization procedures have often been used to determine a liminted set of parameters. However, these consisted of smaller data sets. Other research presents a system approach to optimizeing parameters for the neural network. For this study, the amonut of data is significant and a limited optimization is performed. Training the neural network used the Levenberg-Marquardt back-propagation algorithm. The trainer execjuted several times, using fewer than 1000 epochs, runnng in bach data mode. Hyperbolic tangent was used for the activation function for hidden layer. Biases were used along with linear activation for output layer. Final recognition is deduced from the output layer, using linear activation[1].

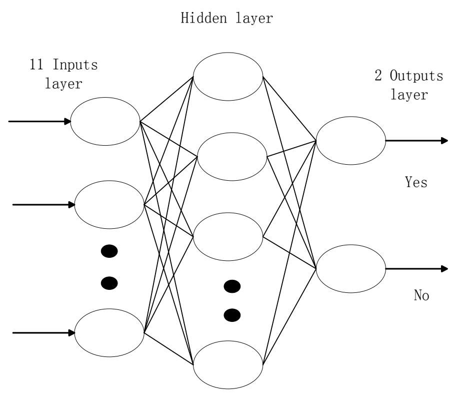

Fig. 7. The structure of BP neural network

Because the feature vector is a 11-D vector, so the input layer consists of 11 nodes. There are 15 nodes in the hidden layer, and output layer has two node which is the recognition result.

G. Results

This section describes the detailed time-frequency distribution of finless porpoise signal. These low frequency components based on Hilbert Huang transform ranging from 20 kHz to 60 kHz are first observed, which not appear in the

Fourier transform. These frequency distribution characteristics based on HHT are used for identifying finless porpoise signal.

The identification performance of the algorithm can be evaluated by comparing the auto identification results with the observed results from human operators. 100 groups of finless porpoise signal are used to train the automation identification algorithm. After training, some experimental acoustic data files are used to test the validity of the automatic identification algorithm. Even it is detected by the low signal to noise ratio data files, finless porpoise signals can be detected. The correct identification probability of the algorithm proposed in this paper reaches 90% with highest false positive rate (<92 per hour), according to the human observation on the time-frequency spectrum. So the experimental results show that the presented artificial intelligence identification algorithm can accurately and quickly recognize finless porpoise acoustic signals.

IV. Discussion and Future Works

A. Discussion

After decades of development, artificial intelligence technology has been relatively mature and has been applied to all aspects of signal processing. The passive recognition is one of the difficult problems in the filed of underwater signal processing. The application of artifical intelligence technology will promote the development of underwater acoustic technology.

In recent years, passive acoustic is becoming a frequently used tool in monitoring marine mammal surveys for study of behavior, migration monitoring [10]. Passive acoustic methods for Yangtze finless porpoise monitoring and detection have a variety of advantages compared to traditional visual methods.

(1).Passive acoustic methods can be undertaken without consideration of daylight and weather conditions.

(2). Passive acoustic monitoring can detect porpoises with a much higher detection rate, resulting in a higher detection probability [11]. This is ideal for the Yangtze finless porpoises since their group sizes are generally relatively small and the overall densities have declined. Acoustic detections were suggested to be a desirable independent observation method for population surveys of Yangtze porpoise [12].

(3) Results from acoustic monitoring methods can be replicated with the use of the equipments calibrated in the same way. Whereas, visual survey results can be highly variable as they are dependent on experience of observers, weather condition, and many other parameters [13].

B. Improvements

This paper proposed an effective artificial intelligence identification algorithm of finless porpoise signal for the first time. The new method combines Hilbert marginal spectrum, Shannon Entropy and Fourier transform to extract finless porpoise. The identification result indicates that the 11-D recognition feature vector F can well indicate the finless porpoise signal and the recognition system based on BP artificial neural network can accurately identify the finless porpoise signal.

Researchers have mainly focused on the fundamental high frequency from Fourier transform, and the usage of low frequency components from time-frequency spectrum has not been fully examined. In this paper the low frequency components based on HHT are used for identifying finless porpoise. The Shannon entropy is also used for identifying finless porpoise signal.

The passive acoustic system and the recognition algorithm in this paper can be used for long-term monitoring finless porpoise in fixed location and surveying finless porpoise in a mobile method. The new automatic recognition method of finless porpoise has great practical significance for surveying and protecting the Yangtze finless porpoise in the wild .

C. Future Works

(1).The present status of the algorithm permits an offline analysis. Adaptation of the algorithm for real-time application will make it indispensable for survey of finless porpoise populations in coastal regions.

(2).More Yangtze finless porpoise data will be studied in the near future. It is very meaningful to understand the acoustic signals emitted from finless porpoises. If we understand the meaning of finless porpoise signal, we will be able to understand the behavior of the finless porpoise, and be able to talk to finless porpoises. That will be much more useful for protecting the endangered species. The understanding of the acoustic signal will help us develop better sonar equipment.

Acknowledgment

The signal acquisition experiments of Yangze finless porpoise were under a permit issued by the Tongling River Dolphin National Reserve, China. This project was supported by National Nature Science Foundation of China (10904159). The authors are grateful for the help and assistance provided by Ran Chen, Bajin Zhang.

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