

VLF Waves Characterization: Wavelet Feature Extraction Method

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Abstract: *In an effort to provide a more efficient representation of the very low frequency (VLF) signal, the application of the wavelet analysis is considered. This research presents an effective and robust method for extracting features for VLF processing. Based on the time-frequency multi-resolution property of wavelet transform, the input VLF signal is decomposed into various frequency channels. The major issues concerning the design of this Wavelet based VLF recognition system are choosing optimal wavelets for VLF signals, decomposition level in the multilevel 1-D wavelet decomposition, selecting the feature vectors from the wavelet coefficients. More specifically classification of various VLF signals using the Wavelet decomposition is described. By this effort we find the different features for the various VLF signal*

Keywords: Chorus, Feature extraction, Hiss, Very low frequency, Wavelet transforms, Whistler

1. Introduction

VLF emissions are natural radio phenomena, whose origin is from magnetospheric sources or in man-made sources such as VLF transmitters. For Space weather studies the investigation of VLF data provides an influential tool for remote sensing of the processes in the magnetosphere. In recent year the prediction of earthquake by VLF waves also the point of study. During the earthquake effect analysis two events are mainly under observation one is hiss and other is chorus (Rodge et al, 1999a), they are the important categories of magnetospheric VLF emission with whistler (Helliwell, 1965; Sazhin, 1982; Hayakawa et al., 1990; Sazhin and Hayakawa, 1992; Hattori and Hayakawa, 1994). Chorus are structured and discrete Its frequency and hiss are unstructured, on the other hand whistler are descending and ascending tones generated through the lighting discharge and which have propagated through the magnetosphere (Storey, 1953). They all have specific characteristics with respective time and frequency, one can be identified it by the spectrograms or by hearing its sound. Above mention studies need continues observation of this phenomena. It created the importance of managing a continuous flow of data through automation of the analysis and classification process. Automation is possible by the machine learning that required a specific representation and characterization. In the past many scientists were working on automatic detection of VLF emission (Buzzi,2006; Linchtenbeger et al., 2008; Ferencz et al., 2009; Golden et al., 2011;Ferencz et al., 2014) by analysis of the spectrogram of VLF signals. As we know that the VLF signals are non-stationary signals and spectrogram is constructed by using Short Time Fourier transform (STFT) in which signal segment within the window function is assumed to be stationary (Akay,1997). Therefore the spectrogram is not suitable for the characteristics of these VLF signals for the automatic signal classification system which is employed by Buzzi, 2006 for the whistler detection. In geophysical process the signals are non-stationary so for characterization of the signals scientist use wavelets transform (Kumar and Efi, 1994). The wavelet transform is a means that converts a signal into a different time frequency

segment. This conversion reveals the characteristics hidden in the novel signal by noticing changes which arise rapidly in a signal as well as changes which occur over a longer duration in the signal. So for the characteristic and extraction of the feature we consider the possibility of providing a unified wavelet-based feature extraction tool which is designed to resist optimally with the whistler, hiss and chorus characteristics particular to VLF wave, in the most computationally efficient manner.

In an effort to offer a more effective representation of the very low frequency (VLF) emission, the privilege of the feature extraction based on an effective and robust method for extracting features for VLF signals. Feature extraction methodologies analyze signals to extract the most prominent features that are representative of the various classes of VLF signals. The main aim of feature extraction is to obtain the further information's from the VLF signal based on the time-frequency multi-resolution property of wavelet transform; the input VLF signal is decomposed into various frequency channels. A major issue concerning the design of the VLF recognition system is choosing optimal wavelets for VLF signals, decomposition level in the multilevel 1-D wavelet decomposition, selecting the feature vectors from the wavelet coefficients. The Solution of this problem is also discuss in the work. This method is very useful for the specifically automatic classification of various VLF signals using the Wavelet decomposition.

2. Theoretical Consideration

For the Feature extraction we employ audio parameter with discrete wavelet transform .Thus, the detail of both are given below:

2.1 Discrete Wavelet Transform

A function $f(t)$ could be inscribed as a series expansion in terms of the scaling function and wavelets by (Steendam and Moeneclae,2001)

$$f(t) = \sum_{p=p_0}^{\infty} \sum_{q=-\infty}^{\infty} a_{p_0}(q) \phi_{p,k}(t) + \sum_{p=p_0}^{\infty} \sum_{q=-\infty}^{\infty} b_{p_0}(q) \psi_{p,q}(t) \quad (1)$$

Where $\phi_{p,k}(t)$ is known as scaling function and $\psi_{p,q}(t)$ denotes the wave function. In this development, the first summation offers a function that is a low resolution or coarse approximation of $f(t)$ at scale p_0 .

Table 1 Feature vector after the applying SFS. S1, S2....S100 denotes the signal. SF11, SF12 ...SF17 represent the feature of S1 signal. Similarly SF21 to SF27 denotes the feature of signal S2 and so on. F1 to F7 is depicted the feature number.

For every cumulative p in the second summation, a higher or finer resolution function is summed, which improves details. The choice of p_0 sets selected those coarsest scale whose space is spanned by $\phi_{p_0,q}(t)$. The residual part function is spanned by the wavelets giving the high-resolution details of the function. The set of coefficients in the wavelet expansion signified by equation 1 is called the discrete wavelet transform (DWT) of the function $f(t)$. These wavelet coefficients, in certain conditions, can completely explain the original function, and in a way alike to Fourier series coefficients, can be used for analysis, approximation, filtering and description. If the scaling function is well performed, then at a high scale, samples of the signal are very near to the scaling coefficients. As state before, for well-mannered scaling or wavelet functions, the samples of a discrete signal can approximate the highest attainable scaling coefficients. It is revealed that the scaling and wavelet coefficients at scale p are associated to the scaling coefficients at scale $(p + 1)$ by the next two relations which given below

$$a_p(q) = \sum_m h(n - 2q) a_{p+1}(n) \quad (2)$$

$$b_p(q) = \sum_m g(n - 2q) b_{p+1}(n) \quad (3)$$

Here h and g indicates the low-pass and high-pass filters consistent to the coefficients $h(n)$ and $g(n)$ respectively. By the DWT we decompose the VLF signals up to three level and get three details (D1, D2, D3) and one approximation (A3) coefficients

2.2 Formation of feature vector

After the DWT of VLF signals in order to improve the correctness in classification of signal, it is important to select good features that can capture all the characteristics of VLF signal. The VLF signals are audio-frequency phenomenon (Allcock, 1957) therefore at this point one can be choose those feature which are quantify for audio signal characterization. Numerous feature are available which provide help for discrimination. But we used time-frequency domain features to reveal the maximum information for the formation of feature vector. We used those audio features which illustrated by Giannakopoulos and Pikrakis, 2014. We have use 13 parameter for the each decomposition level (DL). The detail description of audio feature is given in Table 2 for the one DL.

Table 1 Audio Parameter with mathematical formula

Parameter Name	Mathematical Formula
Zero Crossing Rate	$Z_i = \frac{1}{2} \sum_{n=2}^N \text{sgn}(x(n) - \text{sgn}(x(n-1))) \frac{F_s}{N}$
Short time energy	$EE = \sum_p P_p^{(l)} \cdot \log_2 P_p^{(l)}$
Energy Entropy	$E = \frac{1}{N} \sum_{n=0}^{N-1} x_n^2$
Spectral centroid	$sc = \frac{\sum_{k=0}^{K-1} f_k X_k}{\sum_{k=0}^{K-1} X_k}$
Spectral Spread	$ss = \sqrt{\frac{\sum_{k=0}^{K-1} X_k (f_k - sc)^2}{\sum_{k=0}^{K-1} X_k}}$
Spectral Entropy	$SE = -\frac{\sum_{k=0}^{K-1} X_k \cdot \log(X_k)}{\log(K)}$
Spectral Flux	$\sum_{k=1}^{R_k} X_k^2 = 0.90 \sum_{k=1}^K X_k^2$
Spectral Roll off	$sflux = \sqrt{\sum_{k=0}^{K-1} (X_{k,t} - X_{k,t-1})^2}$
MFCCs	$MFCC_m = \sum_{j=0}^{M-1} \left\{ \log(E_j) \cos\left[\frac{\pi}{2} \left(j - \frac{1}{2}\right)\right] \right\}$

Using above parameter for the each decomposition we form a feature vector. The feature vector of the first D1 is shown in Table 3. In this way we have calculated the feature vector for the D2, D3 and A3. Finally arrange them in the below given form

$$F = \begin{bmatrix} DF1 \\ DF2 \\ DF3 \\ AF3 \end{bmatrix}$$

Where the DF1 is a feature vector of D1, similarly DF2 and DF3 denotes the feature vector of D2 and D3 respectively and the feature vector of A3 is represent by the AF3. Thus dimension of F is 84 by 1.

Table 2 Feature Vector for the first detail

DLs	Feature No.	Feature Name	Feature Vector (DF1)
D1	F1	Zero Crossing Rate	21 by 1
	F2	Short time energy	
	F3	Energy Entropy	
	F4	Spectral centroid	
	F5	Spectral Spread	
	F6	Spectral Entropy	
	F7	Spectral Flux	
	F8	Spectral Roll off	
	F9-F21	MFCCs	

2.3 Feature selection of VLF signals

By the above discussion we get the 84 feature for characterization of VLF signals which contains many features that are either redundant or irrelevant and it is necessary to mute of them. Feature selection method reduced the dimension of the data due to that accuracy, predication performance and better understanding of the feature extraction method have improved (Guyon and Elisseeff, 2003). These methods are not similar as the dimensionality reduction method. Because such methods creating new combinations of features, where as feature selection methods choose those features which are already present in data with high discrimination ability.

In this study Forward Sequential Feature Selection (SFS)(Doak,1992) technique in a wrapper fashion is used for fine feature selection. Quadratic Discriminant Analysis (QDA) as a classifier model provides the support for MCE (misclassification error).These is done by holdout method and cross validation method.

The VLF wave dataset used in the proposed work have been explored from the DEMETER. In total we used 300 different signals, of 1.5sec with sampling frequency 40000Hz, split in three main categories chorus, hiss and whistler denoted as

- Set A-chorus having 100 samples
- Set B-Hiss having 100 samples
- Set C-Whistler having 100 samples

We decompose each signal up to three levels by using Haar wavelet. We obtained VLF high dimensional data which have 84 rows and 100 columns. The data variable consists of 100 observations with 84 features. We apply forward sequential feature selection on 84 features. For that we divide data into a training set of size 270 and a test set of size of 30. The training set is used to choose the features and to fit the QDA model, and the test set is hardened to evaluate the performance of the finally selected feature. During the feature selection procedure, to evaluate and to compare the performance of the each candidate feature subset, we apply stratified 10-fold cross-validation to the training set. It stops when the minimum of the cross-validation MCE is found. The optimum feature set obtained after the completion of algorithm is depicted in Table 3 with general description.

3. Results and Discussions

In these work we have collected the chorus which is obtained from the latitude ~55° with frequency range about<10 kHz, the hiss is consider here is mid-latitude hiss (> 3 kHz).

Table 3: Detail description of selected feature by the SFS to reduce the vector space

Feature no (Before selection)	Feature no (After selection)	Feature Detail		
		DLs	Frequency range of DLs	Feature Name
F4	F1	D1	20 kHz-10 kHz	Spectral Centriod
F7	F2	D1	20 kHz-10 kHz	Spectral Flux
F31	F3	D2	10 kHz-5 kHz	Second MFCC
F48	F4	D3	5 kHz-2.5 kHz	Energy entropy
F49	F5	D3	5 kHz-2.5 kHz	Spectral Flux
F73	F6	A3	2.5 kHz-0 kHz	Second MFCC
F74	F7	A3	2.5 kHz-0 kHz	Third MFCC

and ELF hiss(<2 kHz) between the latitude 55° to 40° and the whistler(whistler train) are collect from the mid latitude.

In VLF spectrogram (Onishi et al., 2010) the VLF emission are describe special structured and occurs in different frequency band within ~20kHz.(Storey, 1953;Taylor and Gurnett, 1968; Dunckel and Helliwell, 1969; Sonwalkar, 1995).

Table 4: Feature vector of selected feature for the 100 VLF signals

Signals /feature	S1	S2	S3	S4	.	.	S100
F1	SF11	SF21	SF31	SF41	.	.	SF1001
F2	SF12	SF22	SF32	SF42	.	.	SF1002
F3	SF13	SF23	SF33	SF43	.	.	SF1003
F4	SF14	SF24	SF34	SF44	.	.	SF1004
F5	SF15	SF25	S35	S45	.	.	SF1005
F6	SF16	SF25	SF36	SF46	.	.	SF1006
F7	SF17	SF27	SF37	SF47	.	.	SF1007

Therefore it is must to study each frequency range for the characterization of VLF signals which is possible by the DWT. Accuracy of DWT based feature selection results depends on the choices of the mother wavelet. Hence we decompose D1 and D2level by Haar wavelet (Alfred,1910) and D3 and A3 through bio3.5(Charles,1992) as it has maximum distribution energy at each DL for the VLF signal. After DWT we calculated different parameter with respected to the time and frequency for each DLs and form a feature vector of 7by1 dimension. This feature vector is shown in Table 4.

According to feature vector mention in Table 4, we calculated the feature vector of hiss, chorus and whistler by means of the 100 signals for each VLF emission. The feature vector of each emission is the new feature vector, able to discriminate the VLF signals. From Figure1, it is obvious that from feature number one to five, the shape of curve is same but the magnitude of each feature is different for each VLF emission plotted in Figure 1 (a), (b) and (c). From Table 3 we found that at least one feature is selected from each band which plays an important role for characterizing the VLF emissions. Because these bands shows variation in energy and shape with respect to time and frequency for the VLF signals.

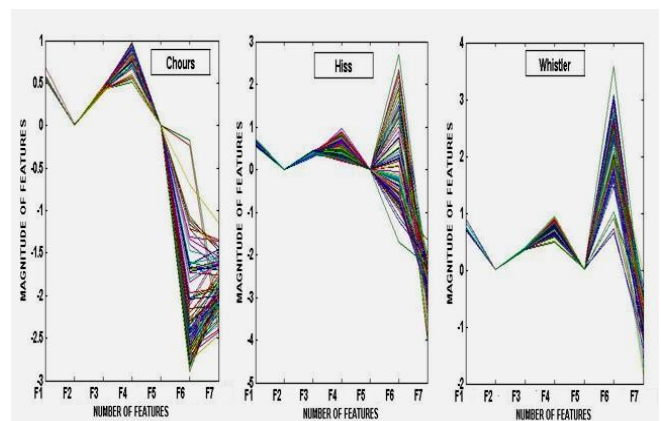


Figure 1: Feature vector plot of Chorus, Hiss and Whistler

during the occurrences of different VLF emission. On analyzing Figure 1 and Table 3 simultaneously, we get the following outcomes:

- i)The first feature is selected from the frequency band 10 kHz-20 kHz is Spectral Centriod (SC). This reveals the brightness of sound signal which helps to distinguish between sounds. Whistler have high value of SC as compared to the hiss and the chorus because most of the whistles are having their nose frequency and upper cutoff

frequency in this range (Helliwell, 1965) and sometimes the amplitude of whistler also approaches to maximum ~15 kHz (Helliwell, 1965). On the other hand the hiss band have upper cutoff in this range but it is actually thermal noise (Gurnett, 1966) causing a low SC. The chorus is not reported in this frequency range (e.g. Sazhin and Hayakawa, 1992; Manninen et al., 2012).

ii) Spectral Flux (SF) is the second feature and its value for each VLF emission is very low. This illustrates that the local spectral change is very low with respect to the frequency, in frequency band 10kHz-20kHz. In this frequency band only the upper cutoff frequency whistler (Carpenter, 1968) and hiss is present which are not showing much variation with respect to the frequency.

iii) The third feature, second MFCC which is selected from the 10 kHz-5 kHz band. It shows value of the amplitude for lower frequency of this band (~6 kHz). For the whistler and the chorus value of MFCC is same for all signals but for the hiss variations are prevalent since its intensity varies with time and frequency (e.g., Gurnett, 1966; Sonwalkar and Inan, 1988). This band contains the lower cut off frequency of VLF hiss and its intensity is found to increase on enhancing frequency. Thus the MFCC values changes for the hiss only.

In frequency band 5 kHz-2.5 kHz we found that the value of Energy Entropy (EE) for all emission varies from signal to signal. EE is the signature of the distortion in the VLF signal relating to frequency. The whistler and the chorus are the structured emission (Storey, 1953; Sazhin and Hayakawa, 1992) and their frequency is either rise or fall in a particular manner with time. On the other hand hiss is incoherent emission which shows no obvious structure (e.g., Helliwell, 1965). Therefore chorus and whistler undergoes uniform distortion in signal instead of hiss.

iv) The frequency band, 5 kHz-2.5 kHz is an important band and the fifth feature which is selected in these range is SF. SF indicates the spectral change with frequency which is dominant in this range because all the components of VLF emissions are present here.

v) Last two features are selected from frequency band 2.5 kHz to few Hz. They are the second and third MFCC. The feature curve; shape is reverse for chorus as compare to hiss and whistler for this feature. Basically in this frequency range the lower cutoff frequency of whistler ELF hiss and the chorus components are generated (Helliwell, 1965). The selected features are related to the amplitude. When we analyse the curve which is formed by these two features, we found that the chorus show inverted curve as compare to the hiss and whistler, which indicates that the amplitude variations are same for the hiss and whistler. Hence we infer of the fact that the ELF hiss is generated due the lightning as whistler, whereas chorus is formed by high energy electrons (by acceleration) outside the plasma sphere (Horne et al., 2005).

These features are able to characterize the VLF emission is identified by their classification ability. Thus we trace an Andrews plot (details Andrews, 1972) which offers the visual classification of this signals is revealed in Figure 2

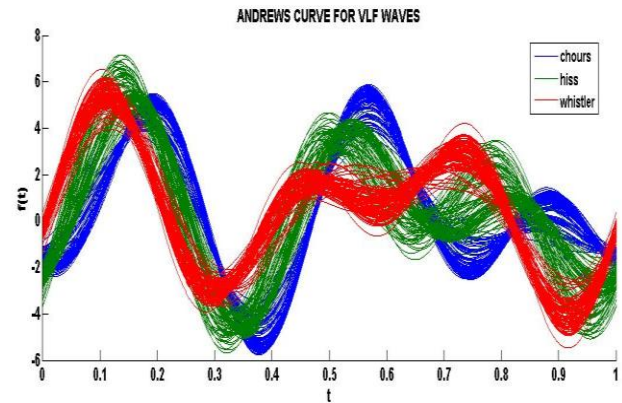


Figure 2: Andrews curve for the classification of VLF waves. Trace on the basis of selected seven feature. Red curve denotes the whistler, green denotes hiss and blue denotes the chorus.

The Andrews curve shows that these features are able to well classify the VLF wave because we can view each VLF emission clearly.

4. Conclusions

The characterization of the three main VLF emissions, the chorus, the hiss and the whistler is a crucial phase in machine learning. So in this chapter wavelet transform based techniques for feature extraction were performed. A well-selected feature set can result in quality representation of VLF wave whereas a wrongly chosen feature set can result in poor representation in machine learning. As VLF signals are non-stationary, the conventional method of frequency analysis is not highly successful in diagnostic presentation. Thus, it is important to reveal the all features which can discriminate the VLF signals in time and frequency domain. So an algorithm for characterization of VLF signal based on DWT and parameter of audio signals has been proposed for feature extraction. In absence of prior knowledge regarding the relevance of the individual features for successful recognition, as much information as possible is included into the feature vector. In addition this method not only provides better representation for the recognition of the three VLF signals-chorus, hiss and whistler also, it can reduce memory space, shorten pre-processing needs and increase computation speed for the machine learning of VLF signal. In future work we involve wave packet decomposition instead of the DWT for the feature extraction.

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