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Performance Analysis of Daubechies Wavelets for Music Signals

Ashutosh Kharb[1], Narender Hooda[2]

[1]BMIET, Sonipat, Haryana

[2]Dy. Registrar, DCRUST, Murthal

***Abstract*—The field of musical signal processing is growing as the improvement in signal processing techniques. Human listener is far superior to understand and classify the information in music signal then automatic technique. Music signal processing is a field in auditory events, where many instruments are played simultaneously. Performance of different daubechies family wavelets is observed for different five music signal. The signal has been decomposed into sub-bands and the features have also been extracted using different Daubechies wavelets. The extracted features have been classified and performance check of different wavelet have been done**

***Keywords*— Daubechies wavelets, Music Signals.**

I. Introduction

Sound and music are common parts of our daily sensory experience. Humans have eyes for the detection of light and colour, so we are equipped with ears for the detection of sound. We rarely take the time to study the characteristics and behaviors of sound. Then we can decide by which mechanisms sounds are produced, propagated. The basis for an understanding of sound, music and hearing is the physics of waves.

There are so many features which are used for instrument identification. Mel-frequency cepstral coefficient is commonly used feature in signal processing. Feature selection techniques are used for optimizing the feature set. Redundant feature are absented from the feature set and dimensionality of the feature set is reduced. In audio signal, most popular method for analyzing music with time-varying energy is the Short Time Fourier Transform (STFT) with different frequency bands. Other useful representations are log-frequency representations and time-chroma representation. Current topics of research in musical signals are: onset detection, periodicity analysis, tempo estimation, beat tracking and recognition of musical instrument in isolation.

An experimental study on feature analysis for recognition of musical instrument with the help of k-NN, Artificial Neural Network ,and Support Vector Machine (SVM) classifier have been performed by J. D. Deng, C. Simmermacher [1].They used perception based features,MPEG-7 timbral feature and MFCC features. They obtained three major feature extraction schemes and analyzed them using a number of feature selection method. They performed experiments on 20 instruments. To know the importance of the feature for classification they used a correlation-based approach. Different types of features are Temporal Features, Energy Features, Spectral Features, Perceptual Features and Harmonic Features. Eronen et al. [2] presented a musical instrument recognition system using 32 spectral and temporal feature. 1498 samples are taken to classify 30 orchestral instruments. Samples are taken from Mc Gill Univesity Master samples CD's. Gaussian and k-NN classifiers are used for classification. Accuracy of system was 95% for group of instruments and 81% for individual instrument. 20 ms frames are used to calculate spectral feature.

Agostinie et al.[3] evaluated a technique for monophonic musical instrument recognition. Database used are taken from McGill University Master samples (MUMs). 1007 tones are used to classify 27 musical instruments. Only spectral feature are used. Experiment is performed on 30 musical instruments. Canonical discriminant Analysis (CDA), Quadrtic Discriminant Analysis (QDA), k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM) were used as classifier. Out of these, QDA was found to be the best with an accuracy of 92.81%.

K. Yoshi et al. [4] developed a method based upon onset detection. This method can detect onset time even if drum sound is overlapped with other sounds. Power spectrogram of drum sound as templates is used for feature extraction. There are two problems: Selection of template and Mixture of many sounds other than drum sound. To solve these problems two methods was proposed, Template Adaption and Harmonic Structure Suppression. Initially seed template for each drum sound is prepared. Template is a power spectrogram in the time frequency domain. Template matching is done only for bass drum and snare drum.

Anti Eronen [5] proposed a musical instrument recognition scheme using Independent Component Analysis (ICA) based transform of feature and discriminatively trained HMMs. The input signal is preprocessed by FIR filters. Frame of 20 ms length with hope size of 4 ms is used. Mel-frequency cepstral coefficient and their first derivative as features are used. ICA is used to transform the feature vector to a basis with maximal statistical independence. Discriminative training improves accuracy mainly with model having low number of omponent in state densities. Only drum samples are used in this paper.

T. Kithara et al. [6] proposed a histrogram based musical instrument recognizer. They used temporal trajectory of instrument existence probability for every fundamental frequency (F0). They calculated instrument existence probability for each target instrument at each point of time frequency plane and hence there is no need for onset detection or F0 estimation.

Arie A. livshin et al. [7] proposed a method in which a number of solo recordings are feeded as training set. Different features say, temporal, energy, spectral, harmonic and perceptual are extracted using Gradual descriptor Elimination (GDE) feature selection algorithm. The reduction of feature is done by Linear Discriminant Analysis (LDA). This is a real-time solo-recognition technique used k-NN with LDA as classifier. The recognition score is 84.6%. The problem arises in this technique is the classification of only single sound at a time. There is a need to recognize multi instrumental music.

A.Livshin et al. [8] presented algorithms for outlier detection, Interquantile Range (IQR), Multiclass IQR (MCIQR) and Self Consistent Outlier removal (SCO). MCIQR computes 162 feature descriptor values and removes 70.1% bad samples. Features are calculated by sliding window of 60 ms with a 66% overlap within the window. Bad sample are usually called outliers. Removal of outliers by listening is hard and time consuming task but this method improve the accuracy of musical instrument recognition process.

D. Fragolie et al. [9] presented a method to classify piano and guitar sounds. It is based upon non-tonal spectral content of a note. It was observed that information contained in note non-tonal part is an important factor for muti-instrument timbre classification. An experiment is performed on 612 isolated guitar note and 926 isolated piano note. Average note duration is 1.8 sec. This method is 100% accurate to classify piano and guitar notes.

T. Kithara et al. [10] proposed a pitch dependent musical instrument identification method. They used an F0 dependent multivariate normal distribution. 129 features are extracted and then PCA and LDA technique are used for dimension reduction. Different parameters i.e. F0-dependent multivariate normal distribution, F0 dependent mean function and F0 normalized covariance are calculated. Further, Bayes decision rule is used for classification. The recognition rate for individual instrument is 75.73 to 79.93 % and for category level is 88.20 to 90.65 %.

II. Proposed Methodology

In our approach, we decompose a music signal to five levels with the help of discrete wavelet transformation. Then energy compaction ration, Skewness and Kurtosis features of signal at each level are calculated. K-NN and SVM classifier are trained for these features hence they are used as a classifier. Wavelet transformation is used to signal to obtain detailed information present in the signal. Time domain signal does not have detailed information, so it is called raw signal. So it must be processed by mathematical transformation for detailed information. Most important information of signal is hidden in the frequency content of the signal. Frequency content of the signal is called frequency spectrum. Basically it shows how many frequencies are present in the signal. Accuracy of classifier is calculated for different wavelet families.

III. Wavelet Transform

The concept of a wavelet was introduced in 1982 by Jean Morlet. The wavelet means small wave and the study of wavelet transform is a new tool for non stationary signal analysis. Immediately, Alex Grossmann theoretical physicists studied inverse formula for the wavelet transform. The joint collaboration of Morlet and Grossmann yielded a detailed mathematical study of the continuous wavelet transforms and their various applications, of course without the realization that similar results had already been obtained in 1950's by Calderon, Littlewood, Paley and Franklin. However, the rediscovery of the old concepts provided a new method for decomposing a function or a signal. A wavelet is a small wave which has its energy concentrated in time and frequency. Wavelet has an oscillating wave like characteristic and has the capability to access simultaneous time and frequency analysis and is fit for transient, non-stationary or time varying phenomena. Translation of a basis function called mother wavelet. Wavelets are mathematical functions with oscillatory nature similar to sinusoidal waves with the difference that they are of "finite oscillatory nature". Waves are smooth, predictable and everlasting, whereas wavelets are of limited duration, irregular and may be asymmetric. Waves are used as deterministic basis function in Fourier analysis for the expansion of signals, which are stationary or time invariant. Wavelets can serve as deterministic or non-deterministic basis for generation and analysis of most natural signals to provide better frequency resolution. Essentially a finite length, decaying waveform, when scaled and translated results in what is called a "daughter wavelet" of the original "mother wavelet". Hence different scaling and translation variables result in a different daughter wavelet from a single mother wavelet

Wavelet transform (WT) is used to analyze non-stationary signals. Non-stationary signals are those whose frequency response varies in time. Wavelets are localized waves and have energy concentrated in time and are suitable for the analysis of transient signals.

$$w_{a,b}\ (t)=\frac{1}{\sqrt{a}}\mathrm{w}\left(\frac{t-b}{a}\right) \quad (1.1)$$

Where 'a' is called scaling parameter and it measures the degree of compression and 'b' is translation parameter which determine the time location of wavelet. If |a|<1 then the wavelet is the compressed version of mother wavelet and corresponds mainly to higher frequency. If |a|>1then the wavelet has the larger time-width then the mother wavelet and corresponds to lower frequencies. So wavelet adapts time-width to their frequencies. A wavelet must satisfy the given equation

$$\int_{-\infty}^{+\infty} |w(t)|^2 \, dt < \infty \qquad (1.2)$$

$$x_w(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} w\left(\frac{t-b}{a}\right) x(t)dt \qquad (1.3)$$

IV. RESULTS AND DISCUSSIONS

Entropy (E), Skewness (S), kurtosis (k) and energy (En) are very important features which are used for signal processing technique. The proposed method has been tested on five different music signals like clarinet violin, drum, conga etc. Important feature like Entropy (E), Skewness (S), kurtosis (k) and energy (En) is calculated at each level of decomposition. The experimental values are given in tabular form. Performance of classifiers has been tested on different pre-processing wavelets. It is observed that SVM is better then k-NN classifier for musical instruments.

Decomposition of different music signal is done. Different daubechies wavelets families are used for decomposition. First level decomposed of signal is obtained after applying DWT to original signal. Second level decomposition is obtained after applying DWT to first level decomposed signal. Third level decomposition is is obtained after applying DWT to second level decomposed signal. Fourth level decomposed of signal is obtained after applying DWT to third evel signal. Fifth level decomposition is obtained after applying DWT to fourth level decomposed signal. Third level decomposition is obtained after applying DWT to second level decomposed
Signal.

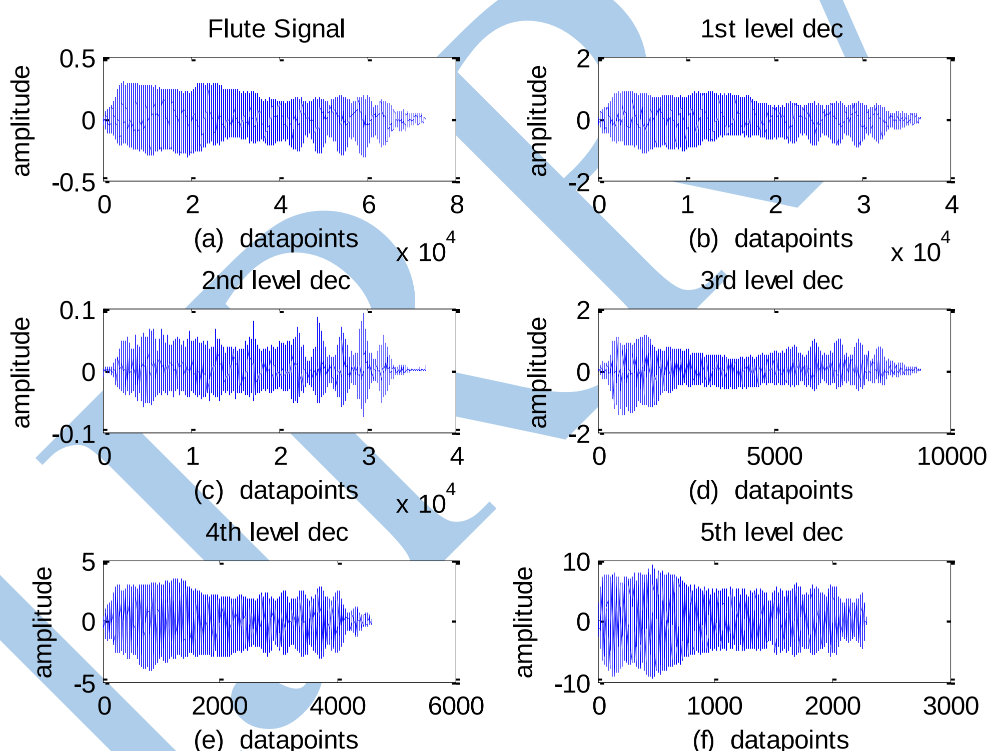

Fig. 1.1 Decomposition of Flute signal

In fig 4.1 decomposition of Flute signal is shown. D4 wavelet is used for decomposition. Fig.4.1 (a) shows original flute signal. In 4.2(b) first level decomposed signal is shown which is obtained after applying DWT to original signal. In fig 4.1(c) second level decomposition is shown which is obtained after applying DWT to first level decomposed signal. In fig 4.1(d) third level decomposition is shown which is obtained after applying DWT to second level decomposed signal. In fig 4.1(e) second level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.1(f) fourth level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.1(g) fifth level decomposition is shown which is obtained after applying DWT to fourth level decomposed signal.

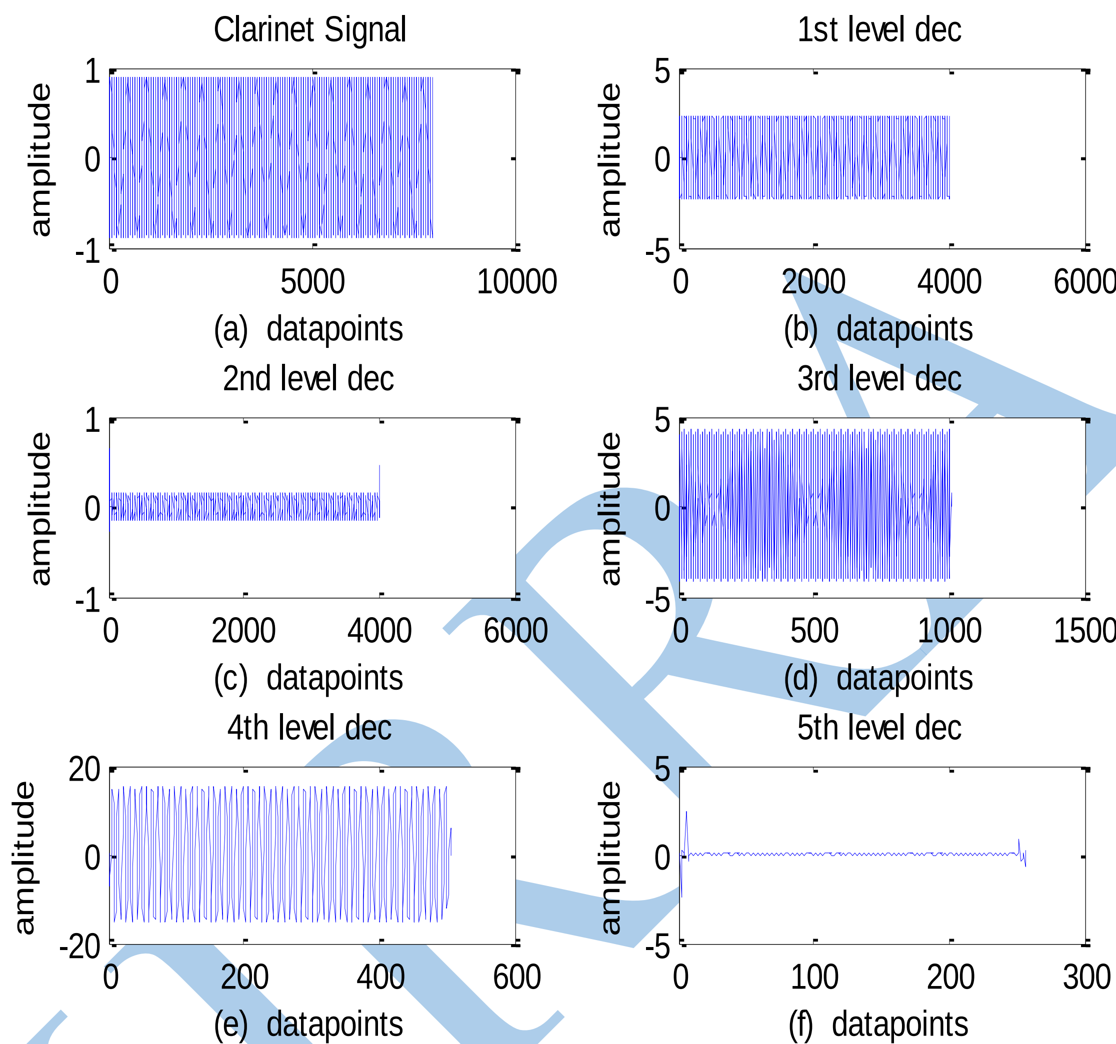

Fig 1.2 Decomposition of Clarinet signals

In fig 4.2 decomposition of clarinet signal is shown. D4 wavelet is used for decomposition. Fig.4.1 (a) shows original flute signal. In 4.2(b) first level decomposed signal is shown which is obtained after applying DWT to original signal. In fig 4.2(c) second level decomposition is shown which is obtained after applying DWT to first level decomposed signal. In fig 4.2(d) third level decomposition is shown which is obtained after applying DWT to second level decomposed signal. In fig 4.2(e) second level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.2(f) fourth level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.1(g) fifth level decomposition is shown which is obtained after applying DWT to fourth level decomposed signal.

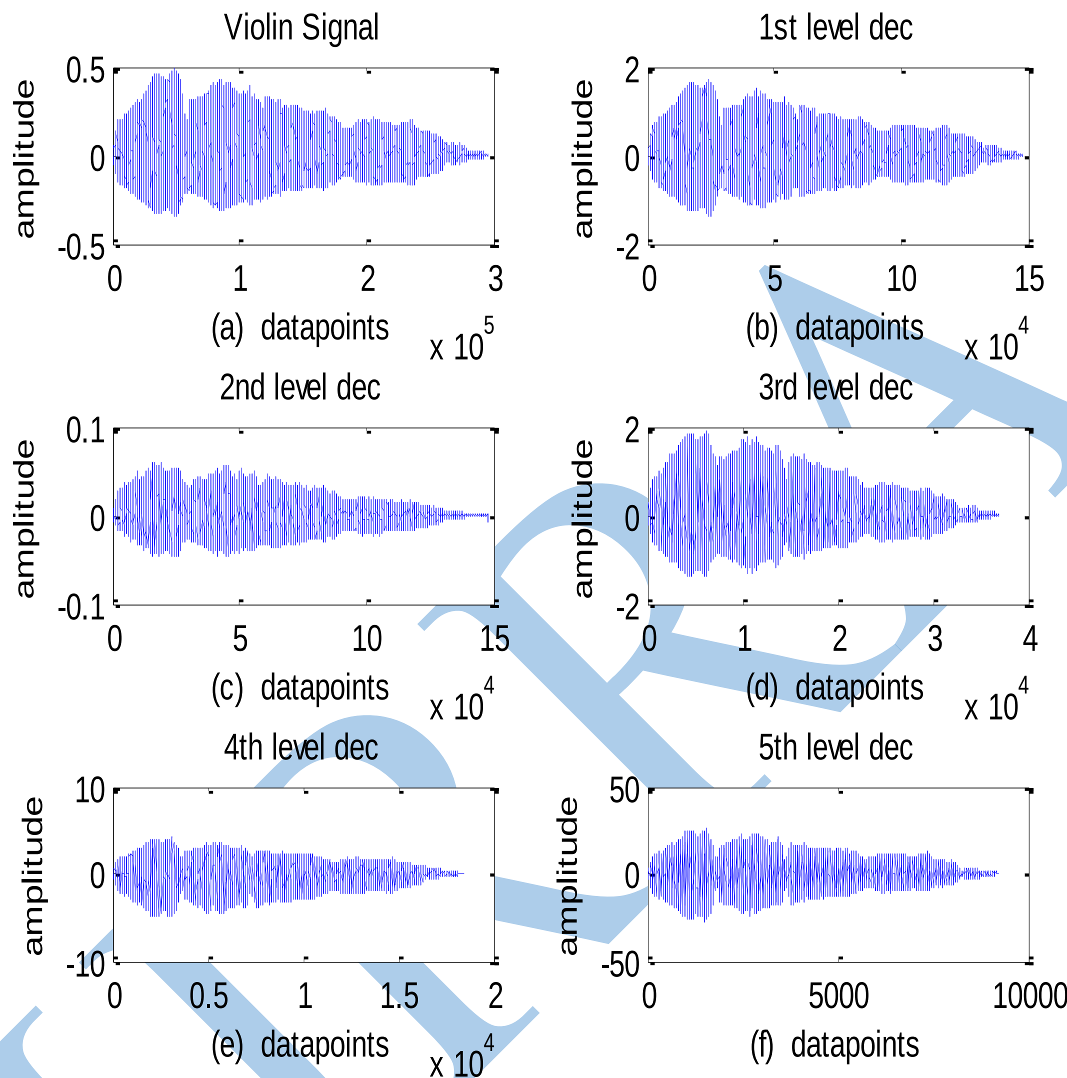

Fig. 1.3 Decomposition of violin signal

In fig 4.3 decomposition of violin signal is shown. D4 wavelet is used for decomposition X-axis has data points of decomposed signal. Y-axis has amplitude of the decomposed signal. Fig.4.3 (a) shows original flute signal. In 4.3(b) first level decomposed signal is shown which is obtained after applying DWT to original signal. In fig 4.3(c) second level decomposition is shown which is obtained after applying DWT to first level decomposed signal. In fig 4.3(d) third level decomposition is shown which is obtained after applying DWT to second level decomposed signal. In fig 4.3(e) second level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.3(f) fourth level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.3(g) fifth level decomposition is shown which is obtained after applying DWT to fourth level decomposed signal.

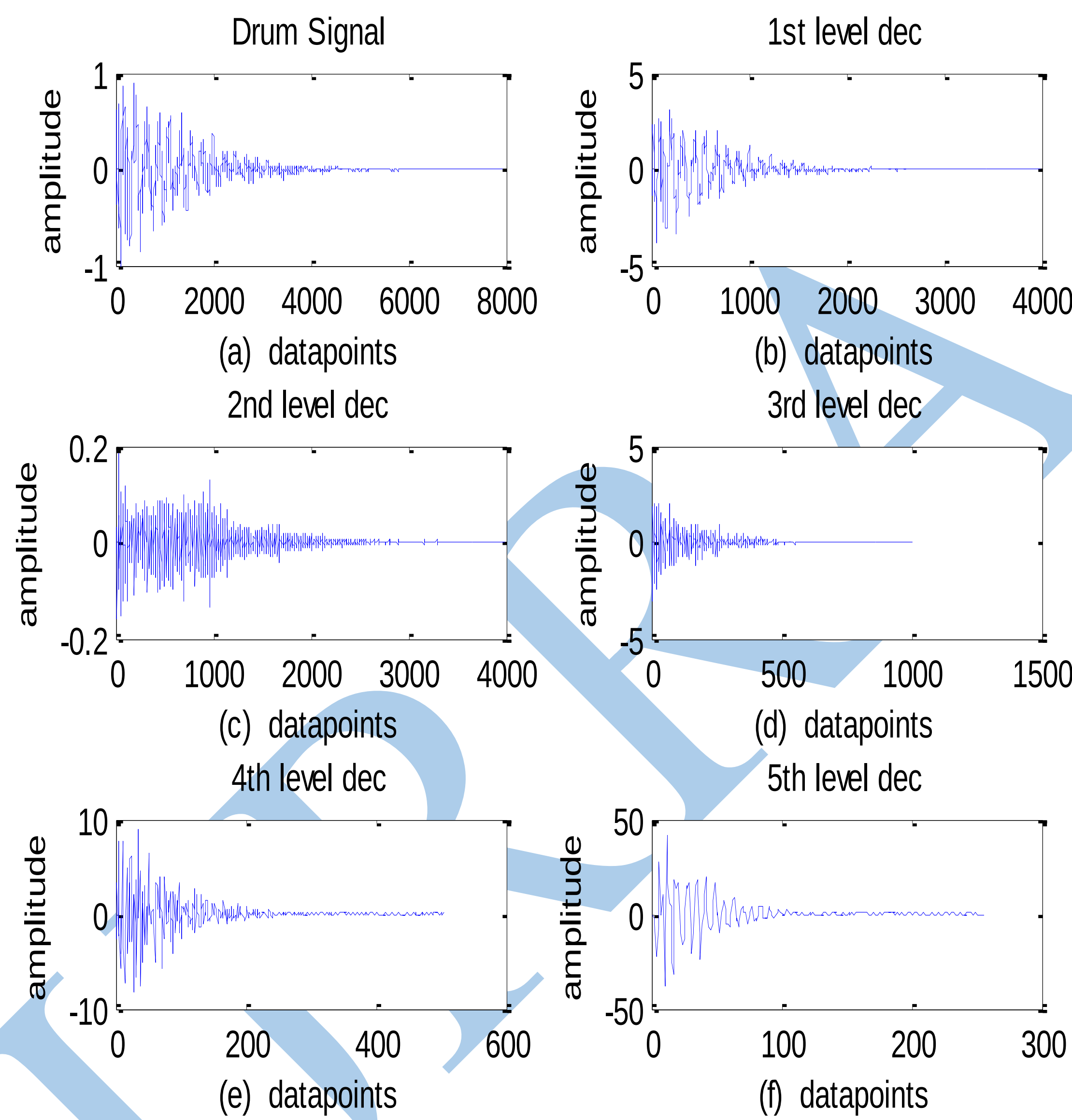

Fig. 1.4 Decomposition of Drum signal

In fig 4.4 decomposition of Drum signal is shown. D4 wavelet is used for decomposition X-axis has data points of decomposed signal. Y-axis has amplitude of the decomposed signal. Fig.4.4 (a) shows original flute signal. In 4.4(b) first level decomposed signal is shown which is obtained after applying DWT to original signal. In fig 4.4(c) second level decomposition is shown which is obtained after applying DWT to first level decomposed signal. In fig 4.4(d) third level decomposition is shown which is obtained after applying DWT to second level decomposed signal. In fig 4.4(e) second level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.4(f) fourth level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.4(g) fifth level decomposition is shown which is obtained after applying DWT to fourth level decomposed signal.

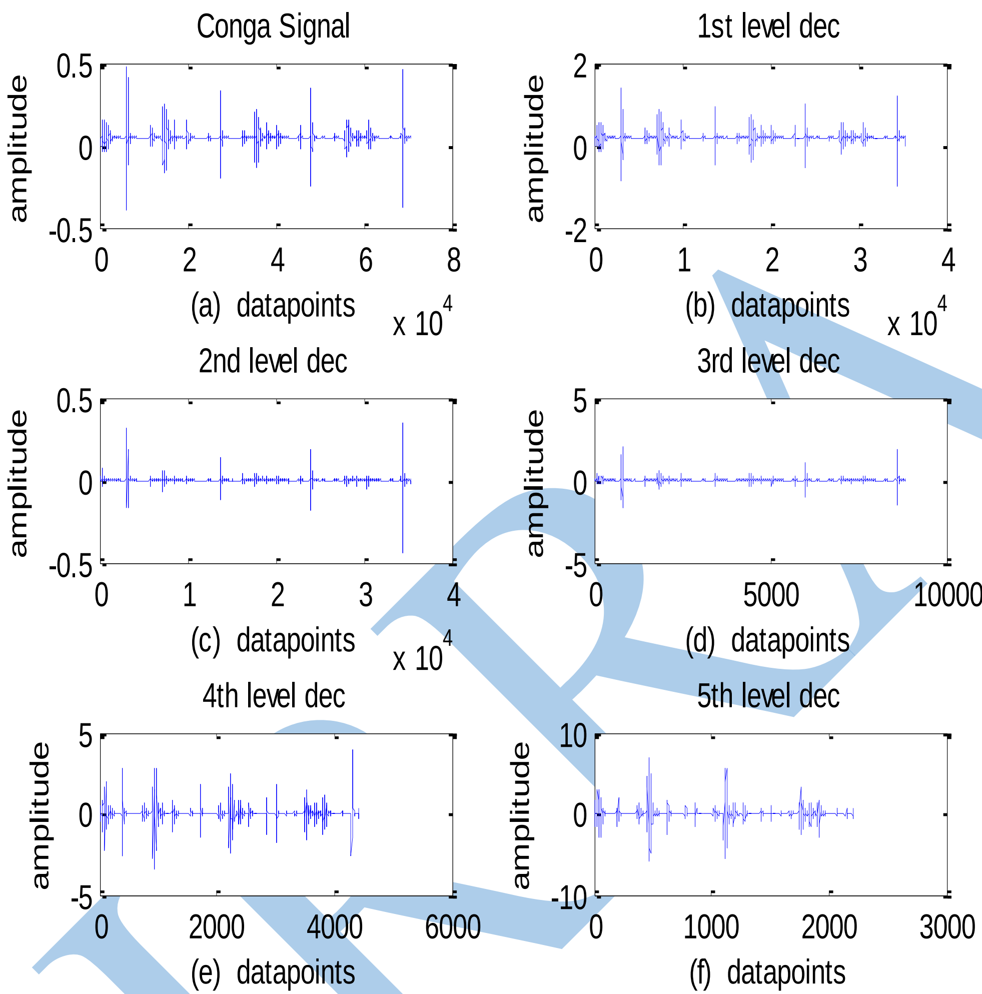

Fig. 1.5 Decomposition of Conga signal

In fig 4.5 decomposition of Conga signal is shown. D4 wavelet is used for decomposition X-axis has data points of decomposed signal. Y-axis has amplitude of the decomposed signal. Fig.4.5 (a) shows original flute signal. In 4.5(b) first level decomposed signal is shown which is obtained after applying DWT to original signal. In fig 4.5(c) second level decomposition is shown which is obtained after applying DWT to first level decomposed signal. In fig 4.5(d) third level decomposition is shown which is obtained after applying DWT to second level decomposed signal. In fig 4.5(e) second level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.5(f) fourth level decomposition is shown which is obtained after applying DWT to third level decomposed signal. In fig 4.5(g) fifth level decomposition is shown which is obtained after applying DWT to fourth level decomposed signal.

Table 1.1 Classification rate for different daubechies wavelet coefficients

Wavelet family	k-NN Classifier	SVM Classifier
Db4	33.33	100
Db6	53.33	93.33
Db8	53.33	93.33
Db10	53.33	80
Db12	53.33	93.33
Db14	53.33	93.33
Db16	46.67	80
Db18	53.33	86.67
Db20	46.67	80

Daubechies wavelet families are used for five levels (L1, L2, L3, L4, L5) of decomposition. Then features (Entropy, Skewness, and kurtosis) are calculated .K-NN and SVM are used for classification. Accuracy of classifier is given in above table. SVM perform better classification than k-NN.

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