Investigative Studies on Timbre of Musical Instruments using Spectral Analysis and Artificial Neural Network Techniques

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Abstract

Spectral content and frequency analysis were carried out on audio signals from various musical instruments using audio signal processing tools and Artificial Neural Network techniques to study the timbre of musical instruments. The nature of peaks produced and their amplitudes for audio inputs of a reference pitch and few melodies were investigated. Significant differences in the frequency spectra were observed which are characteristic of the type of instruments such as string, wind or percussion and rhythmic instruments which provides a means for identification of the category of an instrument. Artificial neural network approach is found to be extremely useful in identification of timbre or tone color of instruments and in identification of instruments. 100% accurate results were obtained on the preliminary investigations.

Keywords *Timbre, Spectral content, neural network, pitch*

I. INTRODUCTION

Sound perception involves assessing the loudness, pitch and timbre of sound also known as tone color or tone quality. The perceived sound quality of a musical note, sound, or tone distinguishes different types of sound production, for eg. Sounds from various sources like animals, birds, bells, horns, moving vehicles, different types of voices, various musical instruments such as string instruments, wind instruments, and so on. While the pitch and loudness of the sources of sound may be same, the characteristic feature that distinguishes the sources is the **timbre**. Timbre is hence a general term for the distinguishable characteristics of a tone and it is mainly determined by the harmonic content of a sound and the dynamic characteristics of the sound such as vibrato and the attack-decay envelope of the sound [1-5].

The vibration of sound waves is quite complex; most sounds vibrate at several frequencies simultaneously. The additional frequencies are called overtones or harmonics. Timbre is caused by the fact that each note from a musical instrument is a complex tone containing more than one frequency. A sound generated on any instrument produces many modes of vibration occurring simultaneously. The vibration that has the slowest rate is called the fundamental frequency and it usually has the highest amplitude.

In other words *quality of auditory sensations* produced by the tone of a sound wave is *timbre*. The timbre of a sound depends on its wave form, which varies with the number of overtones, or harmonics that are present, their frequencies, and their relative intensities.

For eg if a note A in the middle octave is played on an instrument, a note of frequency 440 Hz is obtained, which is the fundamental frequency corresponding to A, and is the same on any instrument tuned perfectly to '**A**'. Along with '**A'** other notes will also appear – at multiples of this frequency with different amplitudes which are known as the *overtones and harmonics*. On a flute which is a wind instrument, these harmonics will be quieter, hence it has very little texture or it is *soft* But on violin, which is a string instrument, some of the harmonics are louder compared to the harmonics of the flute, causing the violin to sound different.[6,7]

Musical instruments are broadly classified into four types namely (i)String instruments, or Thatha Vadya or Chordophones – Sound is produced by the plucking or bowing of a string or Chord which are tied tightly eg., different types of Veena, Sitar, Sarod, Santoor, tanpura, guitar (plucking); Violin, Viola, Sarangi (bowing) (ii) Wind Instruments or Sushira Vadya or Aerophones - Sound is produced due to blowing into an air column with or without reeds – eg., Flute (blowing), piano, electronic key board, Harmonium, Harmonica, accordion(Free Reed Instruments), Saxophone, Clarinet (Single Reed Instruments), Shehnai, Nadaswaram, Oboe, Bassoon (Double Reed Instruments), (iii) Percussion instruments or Avanaddha Vadya or Membranophones – Sound is produced by striking - eg., Different types of

Drums, Mridangam, Tabla, Khanjira, Tavil, Morsing, (iv)Solid Instruments or Ghana Vadya or Idiophones – Sound is produced by the way the instrument vibrates and is caused by striking them, they do not require any tuning and are basically
studied.

Musical notes and melodies were taken as inputs from various types of instruments – *string instruments* - Veena, Mandolin, Violin, Tambura, Sitar, Sarod; *wind instruments* including *single reed*, *double reed* and *free reed* - Flute, Saxophone, Nadaswara, Shehnai; *percussion and solid instruments* - Mridangam, Khanjira, Morsing and Ghatam were investigated by plotting frequency spectrum for audio inputs of several notes and melodies and studying the variation of frequency with amplitude. Several audio inputs from a number of each type of instrument were studied and an overall nature of the spectra is shown in the results.

A. Artificial Neural Network approach

Several audio inputs from various instruments were input to different neural networks and output response was tested after training. Multilayer Percepteron, Generalised Feed forward, Time Delay, Radial Basis function networks were used for training. 70% of the samples were used for training, 10% for cross-validation and 20% for testing. About 206 exemplars were used.
rhythmic – eg., Ghatam, triangles, cymbals, bells, sticks.

By analysing the spectral content of a note it is possible to get information about the type of the instrument.

There are some works on instrument identification using an Artificial neural network approach and using LDA (Linear Discriminant analysis) and other methods. However there is no known research work in terms of direct spectral analysis of audio inputs, particularly on instruments of Carnatic music [6-12]. Hence in the present research a broad spectrum of investigations have been carried out on several audio inputs from different types of instruments to make an analytical study of the nature of frequency spectra of various notes on different instruments.

II. METHODOLOGY

A. Frequency Analysis

Audio inputs from wind instruments, string instruments and percussion instruments were

III. RESULTS AND DISCUSSION

A. String Instruments:

Audio inputs from 6 instruments were studied namely, Veena, Mandolin, Violin, Sarod, Sitar, Tambura. Except in tambura, in all other instruments, the audio input given was the pure fundamental note to which the given instrument was tuned. The instruments were generally tuned at C, D or D# to correspond to the note S. The input signals in each case is shown along with the frequency response (figs 1 – 8). Several inputs from different instruments were used in case of Veena and violin and two such responses are indicated in the graphs.

As expected, the pure note S gives raise to peak of high amplitude at the fundamental frequency of the reference note, i.e., C, D or D# corresponding to the values of 261.6 Hz (at C4), 293.6 Hz (at D4) or 311.1 Hz (at D#4). Along with this the string instruments in general give raise to several harmonics and overtones.

On veena, with a fundamental frequency at D#, several large amplitude peaks are observed at A#4 (P), D#5, A#5, C#6(3N2), D#6. On Mandolin at D#, similarly D# and its multiples, A# and its multiples, F7(4R2), G7(4G3), A7 at the higher octaves are present.

Violin which is bowing instrument also shows several peaks namely, D# and its multiples, A#, G, C#.
Sarod, a popular Hindustani classical instrument which was tuned to a fundamental frequency of C showed even larger number of peaks - C#5, F5, F#5, G#5, E5, G#6, F6 and several higher modes multiples of these.

Sitar (tuned to D) shows a large number of peaks of quite high amplitudes like D5, D6, F#6 (3G3), A6 (P), C7, D7(4S), E7 (4R2), F#7, A7, B7, C8…

Tamboora which was tuned to D# (S) consists of fundamental note at D# along with its higher harmonic at 2D# and the note P corresponding to A# and this gives raise to enormous number of peaks at the harmonics and overtones which resonate with the fundamental frequency.

In general large number of overtones and harmonics are generally observed in the string instruments, more so in sitar, Sarod and Tamboora. One of the reasons for the additional peaks is definitely due to resonance effects with other strings and the sustenance of vibrations of the strings. The timbre of these instruments can generally be called ‘deep’.

B. B.Wind and Reed Instruments

Saxophone is a single reed instrument while shehnai and nadaswaram are double reed instrument. Some Keyboards like the piano keyboard is a free reed instrument. Flute is a blowing instrument. Audio signals from these instruments were studied and the frequency spectra were obtained (figs 9-14). The reference note was at C, D# or A# corresponding to frequencies of 261.6 Hz, 311.1 Hz or 466.2 Hz.

In a flute there are very few peaks seen. Except for the fundamental frequency very few harmonics of reasonable amplitude is present and hence the timbre of the instrument is softer. In instruments like nadaswaram also very few harmonics appear at the higher octaves. Kay board shows typical expected peaks at the reference note, its harmonics at higher octaves and at 3/2 times the fundamental frequency which is a consonant note. Shehnai and saxophone however show few additional peaks at higher octaves and a number of harmonics of the fundamental frequency which give these instruments their characteristic texture which is not soft, can be called ‘hard texture’

C. Percussion and Solid Instruments

Percussion instruments like Mridangam, Khanjira and Morsing were similarly studied at a fundamental frequency of E. It is found that most of the peaks obtained are of almost equal amplitude except for slight variations in the case of morsing. In all the instruments a peak is seen at E. The timbre of the rhythmic instruments can be more ‘metallic’ or ‘hard’ in texture. Mridangam generally has a sustained character of notes. The overtones in the instruments very much depends on the manufacturing.[14]. Table 1 shows the variation of frequency with amplitude for several instruments.

D. Artificial Neural network Studies

Studies using Artificial neural network [15] for identification of timbre of instruments gave 100% results for many neural networks. This indicates spectral content of the frequency – amplitude spectrum is highly indicative of the timbre of the instruments and studies of the spectra helps in assessing the type of instrument. The results from training several neural networks is shown in the fig 21.

1) String Instruments

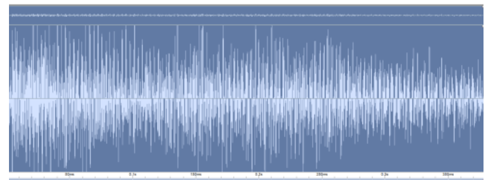

Fig.1 a.Mandolin Input signal of S at D#

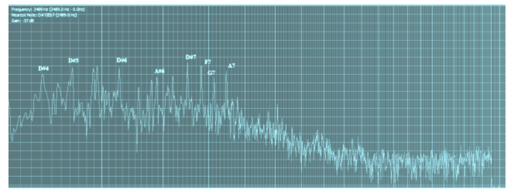

Fig.1 b. Frequency spectrum of S at D#

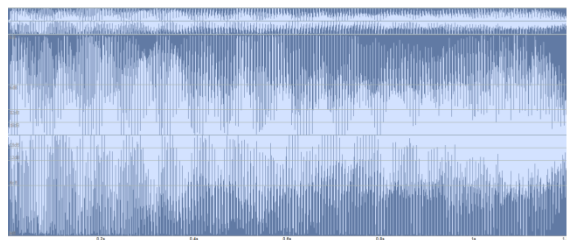

Fig. 2 a..Veena - 1 Input signal of S at D#

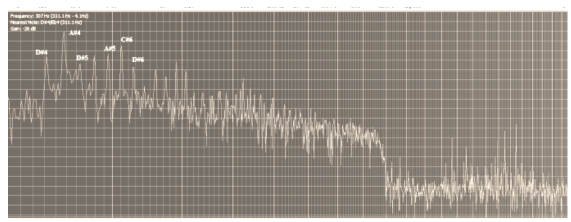

Fig.2 b. Frequency spectrum of S at D#

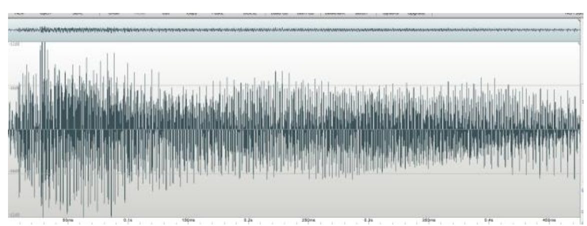

Fig. 3 a. Veena - 2 Input signal of S at E

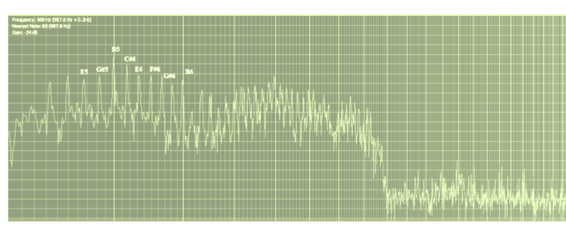

Fig 3 b. Frequency spectrum of S at E

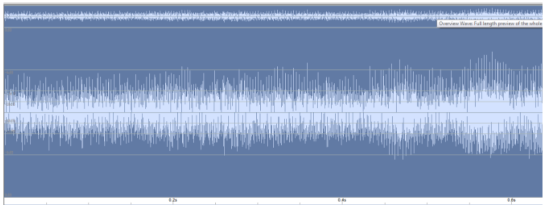

Fig. 4 a. Violin - 1 Input signal of S at D#

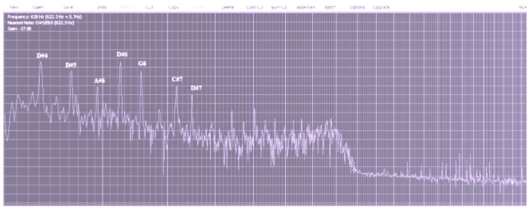

Fig.4 b. Frequency spectrum of S at D#

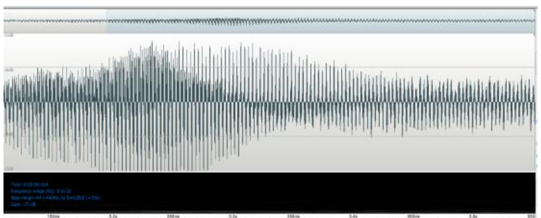

Fig. 5 a. Violin - 2 Input signal of S at D#

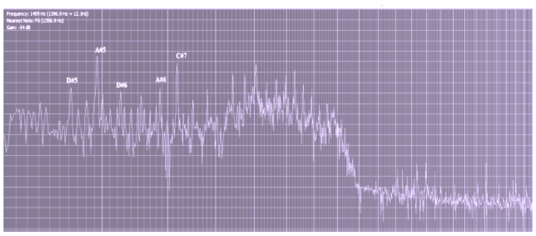

Fig.5 b Frequency spectrum of S at D#

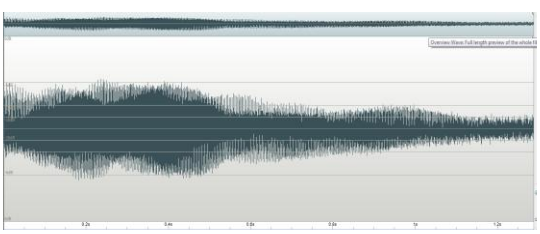

Fig. 6 a Sitar Input signal of S at D#

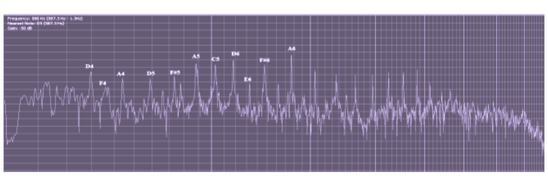

Fig.6 b.Frequency spectrum of S at D#

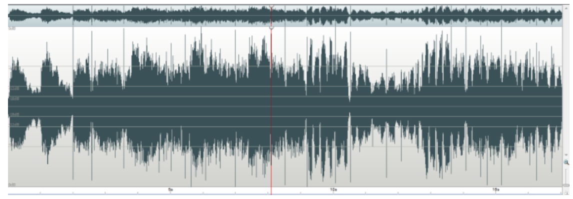

Fig. 7a. Sarod Input signal of S at C

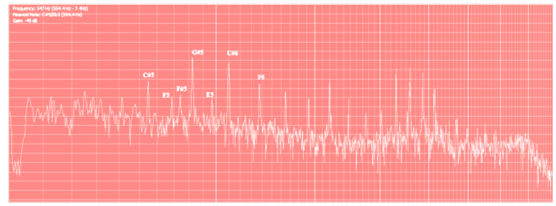

Fig.7 b. Frequency spectrum of S at C

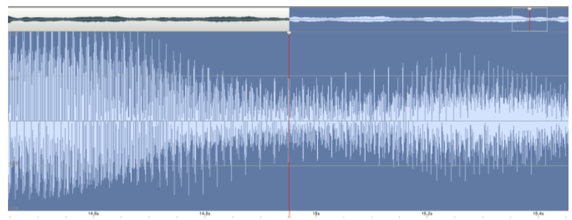

Fig. 8 a. Tanpura Input signal of S(-P-S) at D#

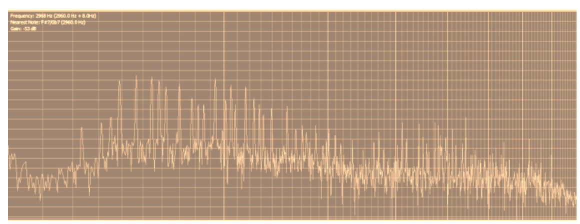

Fig.8 b. Frequency spectrum of S(-P-S) at D#

2) Wind –Reed Instruments

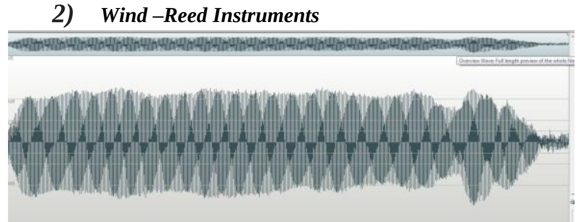

Fig. 9 a. Flute 1 Input signal of S at D#

Fig. 9 b. Frequency spectrum of S at D#

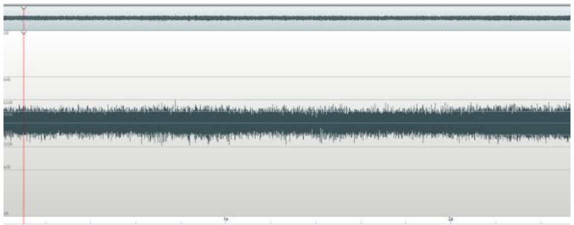

Fig. 10 a. Flute 2 Input signal of S at D#

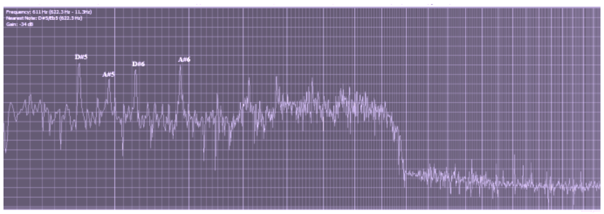

Fig.10 b. Frequency spectrum of S at D#

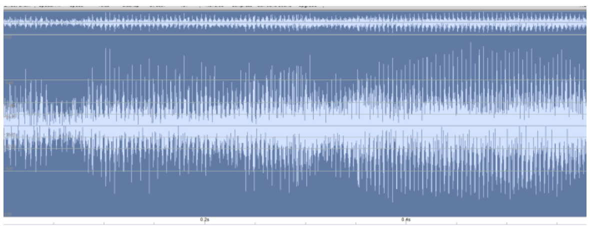

Fig.11 a. Saxophone Input signal of S at A#

Fig.11.b.Frequency spectrum of S at A#

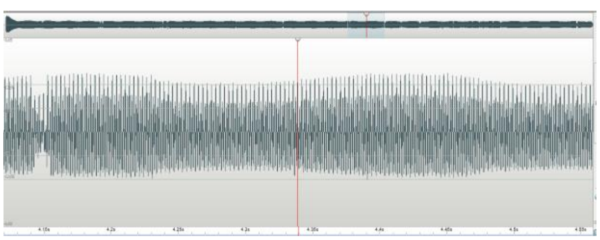

Fig.12. a. Keyboard Input signal of S at D#

Fig.12 b. Frequency spectrum of S at D#

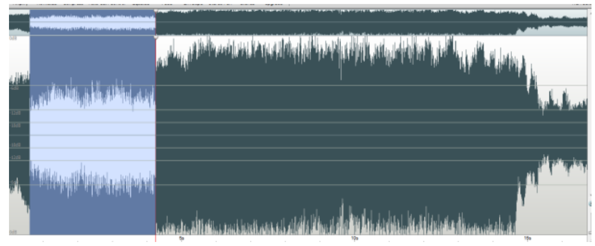

Fig.13 a.. Shehnai Filtered normalized input of S at C

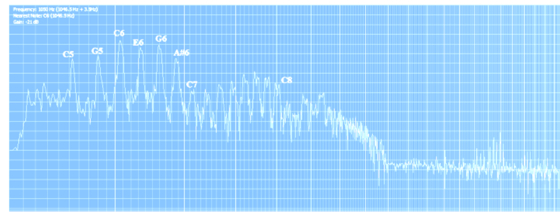

Fig.13 b. Frequency response of S at C

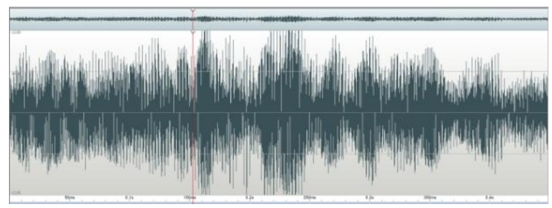

Fig 14 a. Nadaswaram input of S at D#

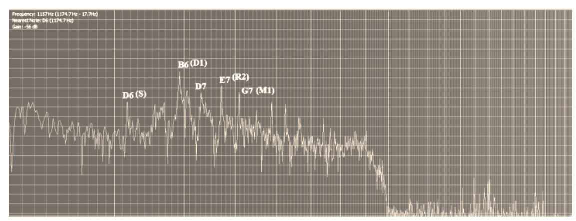

Fig.14. b. Nadaswaram frequency response of S at D#

3) Combination of Instruments

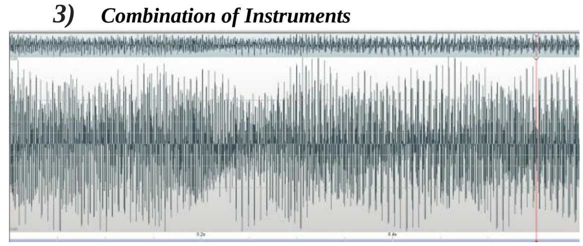

Fig.15.a. S on Veena and Violin played at D#

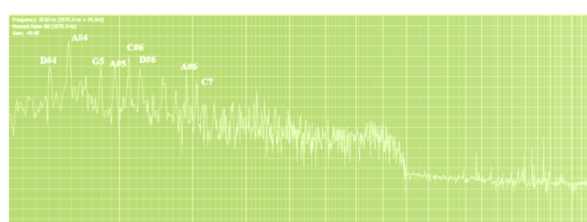

Fig.15 b. Frequency analysis - S note - Veena and Violin at D#

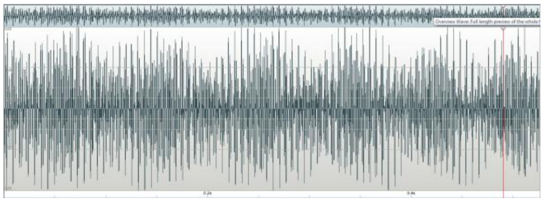

Fig.16. a .S on flute and Veena at D#

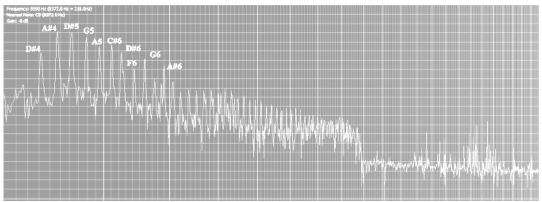

Fig.16 b Frequency analysis - S note - flute and veena at D#

4) Percussion Instruments and Solid Instruments

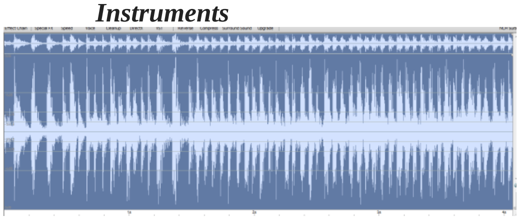

Fig.18 a..Ghatam (solid) input at E

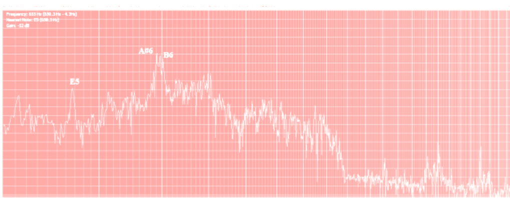

Fig.18 b. Frequency response at E

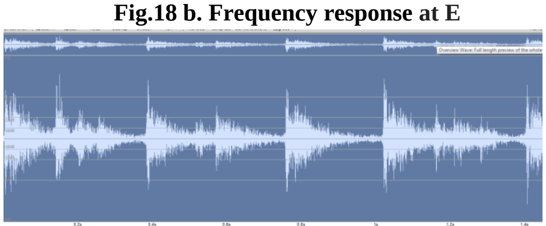

Fig.19 a..Khanjira (percussion) Input at E

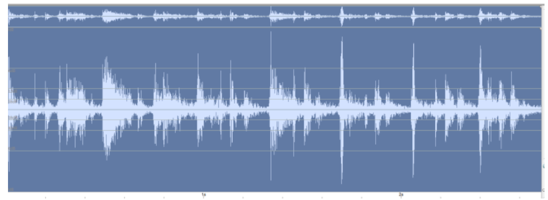

Fig.17a..Mridangam (percussion) input at E

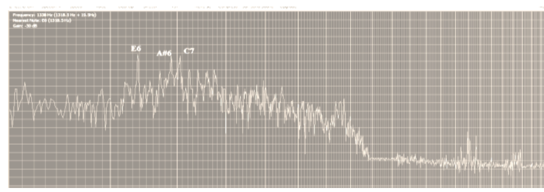

Fig.17 b. Frequency response at E

Fig. 19 b. Frequency response at E

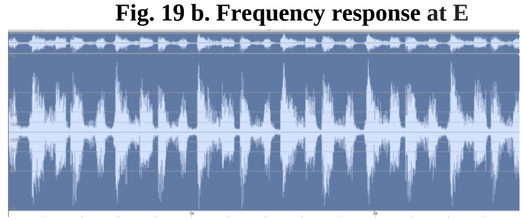

Fig.20 a. Morsing (percussion) Input at E

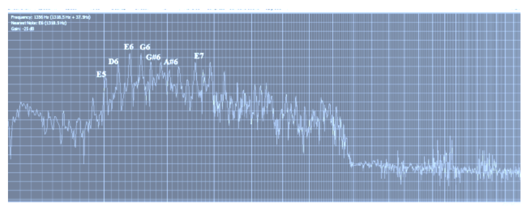

Fig. 20 b. Frequency response at E

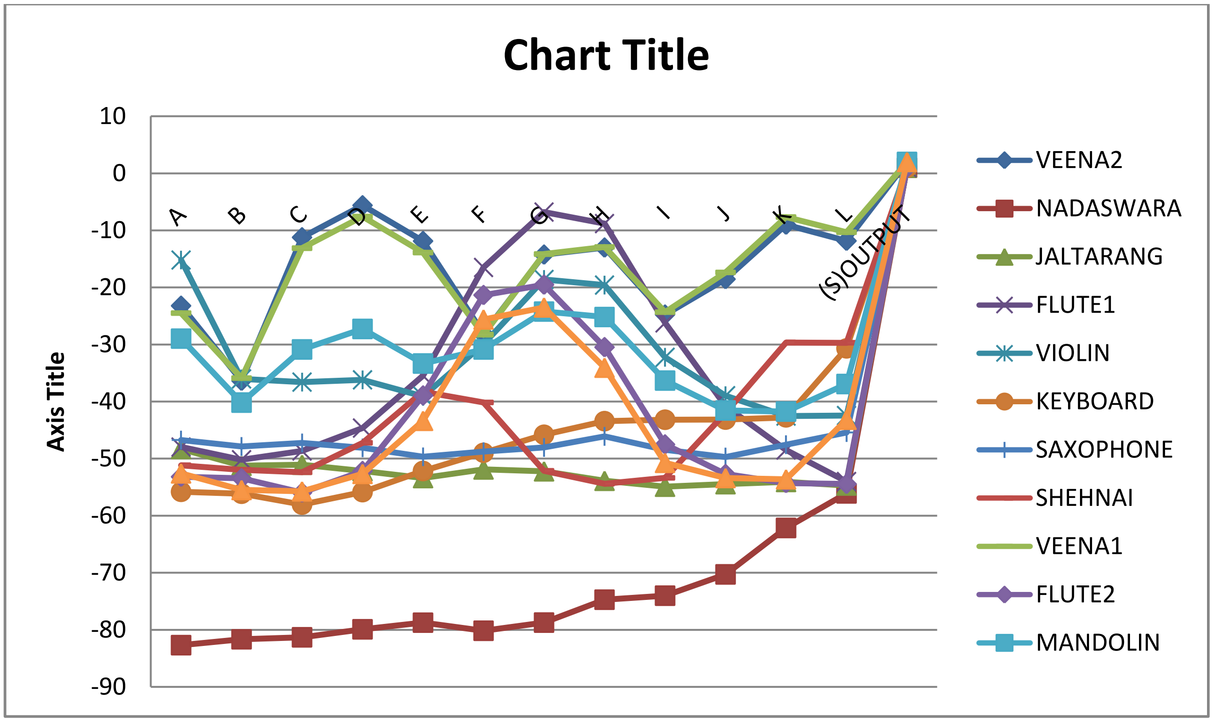

Fig.21 Line Graphs Showing Comparative Variations of Frequency vs. Amplitude for Various Instruments

TABLE 1. TABLE SHOWING VARIATION OF AMPLITUDE WITH FREQUENCY FOR SEVERAL INSTRUMENTS OF DIFFERENT TYPES

X value frequency Hz	Nada swaram Level (dB)	Key board Level (dB)	Flute 1 Level (dB)	Flute 2 Level (dB)	Saxo phone Level (dB)	Shehnai Level (dB)	Jala tarang Level (dB)	Sitar Level (dB)	Mandolin Level (dB)	Veena 1 Level (dB)	Veena 2 Level (dB)	Violin Level (dB)
129.199	-83.97	-66.71	-40.70	-48.85	-54.70	-45.44	-55.60	-46.11	-50.63	-42.89	-41.26	-30.74
172.265	-83.90	-64.36	-41.60	-50.26	-50.36	-46.11	-53.25	-47.79	-43.48	-41.39	-39.84	-31.82
215.332	-85.93	-62.74	-45.45	-49.30	-48.06	-45.61	-54.69	-49.76	-32.53	-46.90	-46.66	-32.15
258.398	-84.71	-61.05	-47.72	-50.11	-51.25	-41.96	-48.08	-48.13	-28.88	-32.44	-31.29	-19.22
301.464	-82.44	-58.95	-47.20	-53.23	-49.61	-44.71	-44.66	-47.75	-24.70	-22.28	-21.04	-11.20
344.535	-82.69	-55.80	-47.96	-53.18	-46.73	-51.17	-48.31	-52.57	-28.97	-24.49	-23.21	-15.18
387.598	-81.66	-56.14	-50.20	-53.45	-47.85	-51.97	-51.24	-55.47	-40.18	-35.88	-36.36	-36.01
430.664	-81.30	-58.05	-48.65	-55.95	-47.24	-52.38	-51.06	-55.71	-30.86	-13.10	-11.22	-36.57
473.730	-79.90	-55.86	-44.64	-52.18	-48.10	-47.24	-52.17	-52.66	-27.28	-7.57	-5.61	-36.17
516.797	-78.74	-52.15	-35.45	-38.93	-49.67	-38.28	-53.40	-43.35	-33.33	-13.88	-11.87	-39.08
559.863	-80.17	-48.97	-16.49	-21.33	-48.77	-40.15	-51.88	-25.59	-30.86	-28.26	-28.10	-29.92
602.930	-78.73	-45.81	-6.77	-19.51	-48.03	-52.14	-52.21	-23.49	-24.22	-14.14	-14.25	-18.58
645.996	-74.72	-43.43	-8.79	-30.46	-46.09	-54.41	-53.88	-34.04	-25.18	-12.89	-13.01	-19.57
689.062	-74.02	-43.17	-26.19	-47.51	-48.44	-53.37	-54.91	-50.72	-36.32	-24.31	-24.76	-32.22
732.129	-70.29	-43.14	-40.79	-52.70	-49.71	-41.98	-54.47	-53.38	-41.55	-17.36	-18.54	-38.95
775.195	-62.14	-42.77	-48.48	-54.28	-47.55	-29.65	-54.08	-53.61	-41.76	-7.64	-9.00	-42.52
818.262	-56.08	-30.67	-54.01	-54.43	-45.41	-29.69	-54.70	-43.17	-36.92	-10.31	-11.83	-42.44
861.328	-52.25	-25.45	-54.46	-54.96	-47.00	-42.03	-56.44	-29.13	-26.12	-28.85	-31.30	-37.07
904.395	-51.47	-31.79	-50.90	-52.94	-47.04	-51.89	-56.61	-28.85	-23.39	-19.60	-19.04	-26.22
947.461	-52.97	-46.43	-50.58	-51.11	-38.01	-50.55	-56.25	-41.89	-24.16	-14.49	-14.12	-25.97

990.527	-55.34	-48.21	-54.13	-49.30	-39.59	-40.23	-56.38	-48.84	-31.84	-21.39	-21.29	-36.91
1033.593	-61.20	-50.58	-50.91	-48.22	-51.36	-25.64	-56.73	-46.05	-35.50	-32.54	-30.69	-38.59
1076.660	-59.01	-52.90	-52.39	-47.60	-52.42	-23.56	-55.17	-45.64	-36.14	-16.92	-14.91	-37.16
1119.726	-52.52	-54.29	-49.84	-36.34	-48.95	-33.36	-53.44	-27.75	-39.55	-15.68	-13.79	-38.82
1162.792	-48.31	-53.70	-38.32	-26.44	-48.29	-50.66	-53.16	-16.43	-37.28	-27.33	-25.63	-37.98
1205.859	-47.57	-54.15	-23.10	-28.53	-46.02	-52.48	-52.37	-17.97	-29.29	-38.28	-36.44	-19.81
1248.926	-47.31	-53.40	-20.78	-43.58	-41.10	-44.75	-54.81	-34.93	-24.43	-30.20	-28.26	-16.40
1291.992	-46.02	-51.17	-30.67	-40.72	-38.03	-28.69	-59.02	-38.25	-30.24	-32.42	-30.60	-25.07
1335.058	-46.17	-49.91	-48.62	-37.77	-41.71	-24.64	-61.33	-35.01	-41.33	-45.61	-45.13	-38.80
1378.125	-45.02	-49.42	-53.03	-45.73	-44.36	-31.78	-60.09	-43.38	-43.93	-37.94	-36.20	-39.50
1421.191	-41.32	-45.09	-53.33	-52.71	-47.31	-48.69	-58.82	-48.90	-44.15	-32.13	-30.12	-40.46
1464.258	-40.10	-44.98	-53.41	-45.75	-47.82	-49.20	-61.09	-40.75	-43.86	-37.51	-35.52	-42.71
1507.324	-38.82	-47.25	-55.35	-48.69	-48.07	-43.60	-61.82	-44.24	-43.92	-44.80	-43.47	-28.83
1550.391	-37.72	-45.30	-55.42	-56.47	-47.60	-26.76	-54.99	-55.71	-38.83	-29.38	-26.89	-23.07
1593.457	-41.17	-42.24	-55.66	-49.56	-45.07	-21.08	-49.28	-55.20	-41.76	-27.25	-24.76	-28.94
1636.523	-45.60	-38.48	-55.81	-48.01	-41.77	-26.29	-52.28	-54.03	-46.77	-37.26	-35.21	-47.56
1679.589	-41.10	-18.23	-55.65	-50.45	-37.40	-45.02	-59.68	-58.99	-42.57	-46.63	-44.14	-47.68
1722.656	-38.38	-13.53	-55.18	-37.02	-38.12	-50.59	-62.37	-45.92	-37.27	-36.76	-34.92	-48.99
1765.723	-37.72	-20.61	-55.37	-31.60	-41.30	-47.96	-64.14	-39.15	-30.94	-37.67	-35.38	-49.92
1808.789	-38.61	-39.26	-43.58	-37.79	-41.25	-34.80	-64.86	-44.25	-31.97	-48.01	-45.56	-47.81
1851.856	-42.53	-42.91	-36.83	-55.64	-38.01	-28.10	-64.71	-61.45	-24.22	-35.99	-34.12	-44.79
1894.922	-48.15	-46.20	-41.61	-49.65	-31.56	-31.28	-64.86	-59.34	-24.39	-27.97	-26.11	-45.70
1937.988	-47.73	-48.24	-56.97	-49.37	-31.29	-45.16	-64.27	-59.06	-37.27	-31.56	-29.98	-49.02
1981.055	-46.28	-46.60	-57.56	-54.82	-36.20	-53.13	-58.92	-58.35	-44.59	-48.46	-47.18	-48.82
2024.121	-46.00	-48.19	-59.19	-55.55	-35.18	-56.36	-57.02	-36.13	-40.10	-37.82	-35.20	-51.18

TABLE 2 SUMMARY OF RESULTS ON TIMBRE STUDIES ON VARIOUS INSTRUMENTS USING DIFFERENT ARTIFICIAL NEURAL NETWORKS

	Training		Cross -Validation		Testing	
Model Name	**MSE**	**Correct**	**MSE**	**Correct**	**MSE**	**Correct**
LR-0-B-L (Linear Regression)	1.44E-26	100.00%	0.207106	100.00%	0.055177	100.00%
PNN-0-N-N (Probabilistic Neural Network)	0.000819	100.00%	154.2824	100.00%	26.41221	100.00%
MLP-1-O-M (Multilayer Perceptron)	29.53298	100.00%	1.772304	100.00%	31.94567	100.00%
LR-0-B-M (Linear Regression)	63.75302	100.00%	19.07905	100.00%	92.11467	100.00%
RBF-1-B-L (Radial Basis Function)	5.921902	100.00%	76.88319	100.00%	36.4711	100.00%
GFF-1-B-L (Generalized Feedforward)	294.3758	100.00%	263.0782	100.00%	412.4508	100.00%
MLPPCA-1-B-L (MLP with PCA)	56.39166	100.00%	0.082338	100.00%	5.520844	100.00%
SVM-0-N-N (Classification SVM)	102.7184	100.00%	24.01545	100.00%	39.59007	100.00%
TDNN-1-B-L (Time-Delay Network)	154.3912	100.00%	72.77482	100.00%	303.3459	100.00%
TLRN-1-B-L (Time-Lag Recurrent Network)	806.8482	100.00%	954.2776	100.00%	680.1075	100.00%
RN-1-B-L (Recurrent Network)	211.8389	100.00%	0.999109	100.00%	284.2176	100.00%
MLP-2-B-L (Multilayer Perceptron)	281.8261	100.00%	293.2937	100.00%	111.4163	100.00%
MLP-1-B-M (Multilayer Perceptron)	70.13439	100.00%	16.03769	100.00%	41.76909	100.00%

MLP-2-O-M (Multilayer Perceptron)	61.17547	100.00%	3.830632	100.00%	121.0158	100.00%
MLP-2-B-M (Multilayer Perceptron)	64.10472	100.00%	29.29173	100.00%	138.4722	100.00%
MLPPCA-1-O-M (MLP with PCA)	35.19001	100.00%	23.83659	100.00%	52.14852	100.00%
MLPPCA-1-B-M (MLP with PCA)	66.28958	100.00%	2.439599	100.00%	126.1463	100.00%
GFF-1-O-M (Generalized Feedforward)	55.90612	100.00%	0.520978	100.00%	12.06767	100.00%
GFF-1-B-M (Generalized Feedforward)	37.3427	100.00%	19.51795	100.00%	42.75641	100.00%
RBF-1-O-M (Radial Basis Function)	26.2072	100.00%	51.15656	100.00%	59.91435	100.00%
RBF-1-B-M (Radial Basis Function)	23.39667	100.00%	23.54892	100.00%	52.1163	100.00%
TDNN-1-O-M (Time-Delay Network)	0.289307	100.00%	87.11817	100.00%	51.74428	100.00%
TDNN-1-B-M (Time-Delay Network)	9.368053	100.00%	133.238	100.00%	113.3534	100.00%
RN-1-O-M (Recurrent Network)	451.1455	100.00%	0.906226	100.00%	1289.965	100.00%
RN-1-B-M (Recurrent Network)	41.7554	100.00%	91.42335	100.00%	332.2876	100.00%
TLRN-1-O-M (Time-Lag Recurrent Network)	0.184904	100.00%	154.8723	100.00%	136.9395	100.00%
TLRN-1-B-M (Time-Lag Recurrent Network)	10.54046	100.00%	112.6665	100.00%	325.3271	100.00%

IV. CONCLUSIONS

Frequency spectra from audio inputs of several instruments belonging to various categories namely stringed-plucked or bowed, Wind- blowing or reed, Percussion and Solid instruments were investigated. Instruments studied were Veena, Violin, Mandolin, Sitar, Sarod, Tambura, flute, nadaswaram, Shehnai, Saxophone, electronic keyboard, Mridangam, Morsing, Khanjira and Ghatam. It was found in general that the number of harmonics and overtones in stringed instruments were significantly larger in number which includes not only the reference pitch and its higher harmonics, and peaks at 3/2 times the fundamental frequency. 3/2 times the fundamental frequency at any pitch denotes the note P in Indian Classical music. It is a consonant note to the fundamental frequency and is hence always present.

In addition string instruments have several strings tuned to other frequencies which resonate when any string is plucked. This can give raise to several other peaks in the form of semitones and microtones which are of considerable amplitude. The additional frequencies are mostly at 9/8, 4/3, 81/64 or 243/128. However, flute and other wind instruments have fewer peaks. Flute in particular has usually only three peaks when the fundamental frequency is played which correspond to the fundamental, its upper octave and at the midpoint between the two which is the note P.

Nadaswaram, Saxophone and other reed instruments have many harmonics at several upper octaves but generally not other overtones. In percussion and solid instruments except morsing, instruments are played by striking and are rhythmic and hence do not show any particular dominant frequency. Hence frequency analysis at the first level can be used to categorise the family of a given instrument by studying the frequency response.

Artificial neural networks can be highly useful in interpreting the timbre of the instrument and this approach can give accurate results for identification of instrument. This approach to identification of instruments is relatively new and very little work has been done hitherto in this area. The techniques of frequency analysis and Artificial neural network offer very new dimensions for the study of timbre or tone colour of an instrument.

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