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ELECTRICAL MACHINES SIGNATURE ANALYSIS USING HMM

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ABSTRACT
This work presents a robust environmental sound recognition system based on digital signal processing technique with system identification. Specific system identification can be activated based on identified sound classes. The computing algorithms of sound features, being the main part of sound recognition system are analyzed. From this point of view, the determination algorithms of Mel Frequency Cepstral Coefficients and Linear Predictive Coding expressing the basic sound features are developed.The training and recognition processes are realized by Hidden Markov Model in the system identification. In this paper the problems observed by number of audio signal features at training the HMM of MFCC and LPC based sound recognition subsystems are investigated. The Power Spectral Density is also applied for each sound signal to unique identification. Identifying the sound classes, type and working asset of system depending upon sound signal can provide significant help in system identification and environmental monitoring. Simulations and experimental in a real world environmental are the object to be achieved to illustrate the performance of the proposed robust sound recognition system.

Keywords
System identification, Sound recognition, Mel Frequency Cepstral Coefficient, Hidden Markov Model, Linear Predictive Coding, Power Spectral Density.

1. INTRODUCTION
The idea of the audio signal processing is to implement a recognizer using MATLAB which can identify a person by processing his/her voice. The MATLAB functions and scripts were all well documented and parameterized in order to be able to use them in the future. The basic goal of our project is to recognize and classify the sounds of different persons. This classification is mainly based on extracting several key features like Mel Frequency Cepstral Coefficients from the audio signals of those persons by using the process of feature extraction using MATLAB. The above features may consist of pitch, amplitude, frequency etc. It can be achieved by using tools like MATLAB. Using a statistical model like Gaussian mixture model and features extracted from those audio signals we build a unique identity for each word for system recognition.

Expectation and Maximization algorithm is used, an elegant and powerful method for finding the maximum likelihood solution for a model with latent variables[1], to test the later sounds against the database of all speakers who enrolled in the database using LABVIEW.There are many motivations in identifying the emotional state of speakers. In human–machine interaction [2], the machine can be made to produce more appropriate responses if the state of emotion of the person can be accurately identified [2]. A HMM speaker independent isolated word recognition system is described. In the system, frames, the EM algorithm, MFCC and Linear Predictive Coding algorithms are used for the classification of the sound space.

In this study the sound features are extracted for different audio signals namely Night Effect Sounds, Electrical Machines sounds, Human being sounds, Vehicles sounds are identified by its sound classes through MATLAB and LABVIEW. Various analyses are carried out to obtain the maximum performance and the results are compared.

2. OVERVIEW OF FEATURE EXTRACTION
Feature Extraction is basic step in sound recognition so that here using the determination algorithms of MFCC and LPC coefficients are extracted the basic audio signal features.

2.1 MelfrequencyCepstralCoefficient
The N FFT magnitude co-efficient are converted to K filter bank values. This is necessary since N = 256 represents too much spectral detailed information and by smoothing the spectrum to only K = 30, or so,

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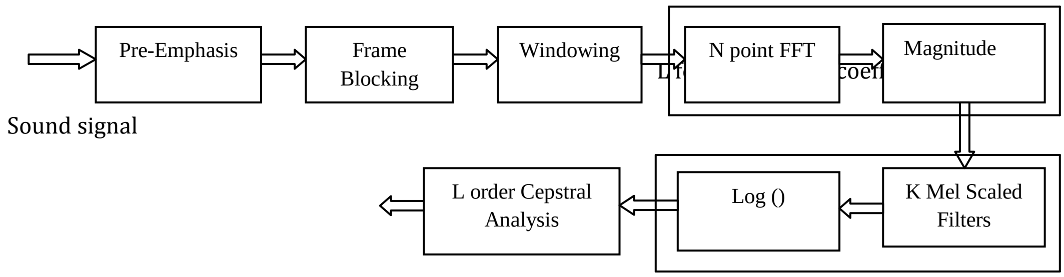

Fig 1:Block diagram of Mel frequency cepstral coefficients

values per frame a more efficient representation is achieved [3]. Furthermore this can be carried out in a perceptually meaningful way by smoothing logarithmically rather than linearly, specifically using a Mel or Bark scale. The filter bank values are derived by cross-wise multiplying the N FFT magnitude co efficient by the K triangular filter bank weighting function from Fig. 1. The centres of the triangle filter banks are spaced according to the Mel scale:

2.2 Linear Predictive Coding

It is one of the most powerful sound analysis techniques, and one of the most useful methods for encoding good quality sound at a low bit rate and provides extremely accurate estimates of sound parameters.The demo consists of two parts; analysis and synthesis. The analysis portion is found in the transmitter section of the system[10]. Reflection coefficients and the residual signal are extracted from the original audio signal and then transmitted over a channel.The synthesis portion, which is found in the receiver section of the system, reconstructs the original signal using the reflection coefficients and the residual signal in fig 2.In this simulation, the audio signal is divided into frames of size 20 ms (160 samples), with an overlap of 10 ms (80 samples).

Each frame is windowed using a Hamming window. Eleventh-order autocorrelation coefficients are found, and then the reflection coefficients are calculated from the autocorrelation coefficients using the Levinson-Durbin algorithm. The original audio signal is passed through an analysis filter, which is an all zero filter with coefficients as the reflection coefficients obtained above.The output of the filter is the residual signal. This residual signal is passed through a synthesis filter which is the inverse of the analysis filter. The output of the synthesis filter is the original signal.

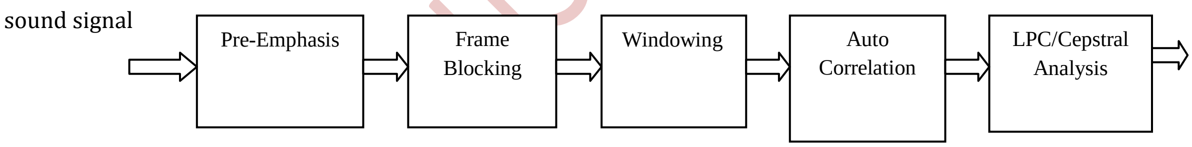

Fig 2: Block diagram of linear predictive coding

2.3 Power Spectral Density

PSD measures power per unit of frequency and has power/frequency units. The PSD data object returned contains among other parameters the spectrum data, the frequencies at which the spectrum was calculated, and the sampling frequency. The average power method uses a rectangle approximation to the integral to calculate the signal's average power using the PSD data stored in the object.The average power method returns the average power of the signal which is the area under the PSD curve.For example shown in fig 3 and 4 for water sound.

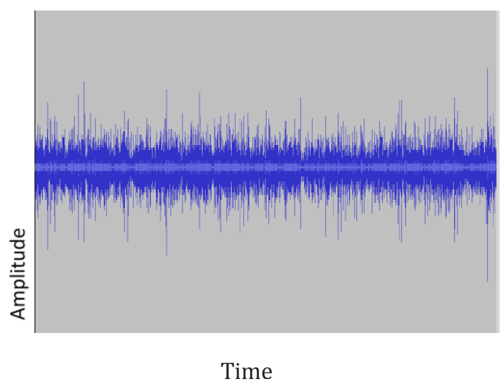

Fig 3: Audio signal for water sound

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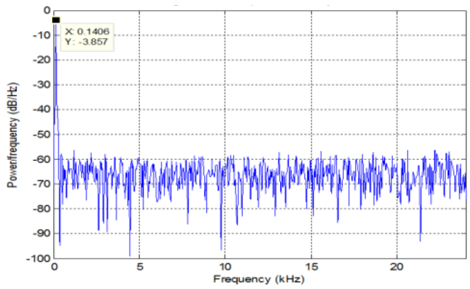
Fig4:PSD for Water Sound



2.4 Hidden Markov Model

The training procedure for HMMs involves an EM algorithm, where the feature vectors are first temporally aligned to the states using a dynamic programming procedure and the aligned feature vectors are used to update the parameters of the state GMM [4]. During the verification procedure, the most probable sequence of states/phones are estimated (again using a dynamic programming procedure) for a given utterance. The scores generated by each state in the most probable sequence are accumulated to obtain the utterance and sound specific likelihood. Because the HMMs rely on the phonetic content of the audio signal, they have been used pre-dominantly in speaker-independent sound verification systems

3 ANALYSIS AND SIMULATION RESULTS

3.1 Different audio signal and its power spectral density

The methods of the PSD data object include plot, and average power. The plot method plots the spectrum data stored in the object. Here the Electrical machines sound are taking and the power value is calculating for four to five for each signal then it will generate the consider range of power values for each type of audio signal in table1 and fig 5.

Table 1. Power Values for Different Audio Signals of The Electrical Machine

Tap 1	19.2754	19.3283	19.3247	19.2708
Tap2	19.2798	19.2493	19.3.14	19.3225
Tap3	19.2549	19.2959	19.3043	19.3113
Tap4	19.2802	19.2957	19.3152	19.2499
Alarm1	0.0719	0.0736	0.0744	0.0733
Alarm2	0.074	0.0732	0.0731	0.0674
Alarm3	0.0686	0.071	0.0688	0.0706
Alarm4	0.0701	0.0693	0.0721	0.0714
Fan1	6.4685	6.4575	6.4796	6.4763
Fan2	6.4914	6.4902	6.4764	6.4678
Fan3	6.4742	6.5093	6.4874	6.4882
Fan4	6.4583	6.4836	6.4904	6.5019
Motor1	3.3328	3.3428	3.34	3.3177
Motor2	3.3403	3.3467	3.3371	3.3268
Motor3	3.3456	3.3118	3.3375	3.3563
Motor4	3.3525	3.3227	3.3207	3.3216

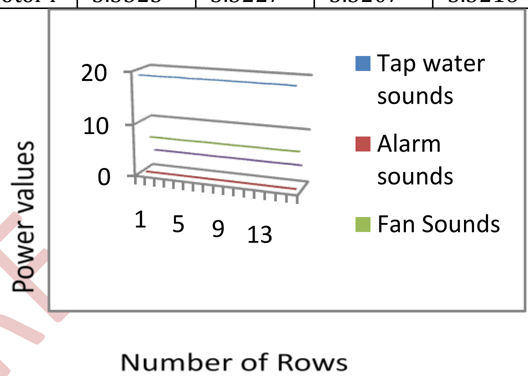


Fig5:Power Value Response Of Different Electrical Machine's Sounds

The power spectral density are calculated at different frequency ranges are shown in below fig6 and also the comparison between power spectral density performance of different audio signal is shown in table2 and fig7.

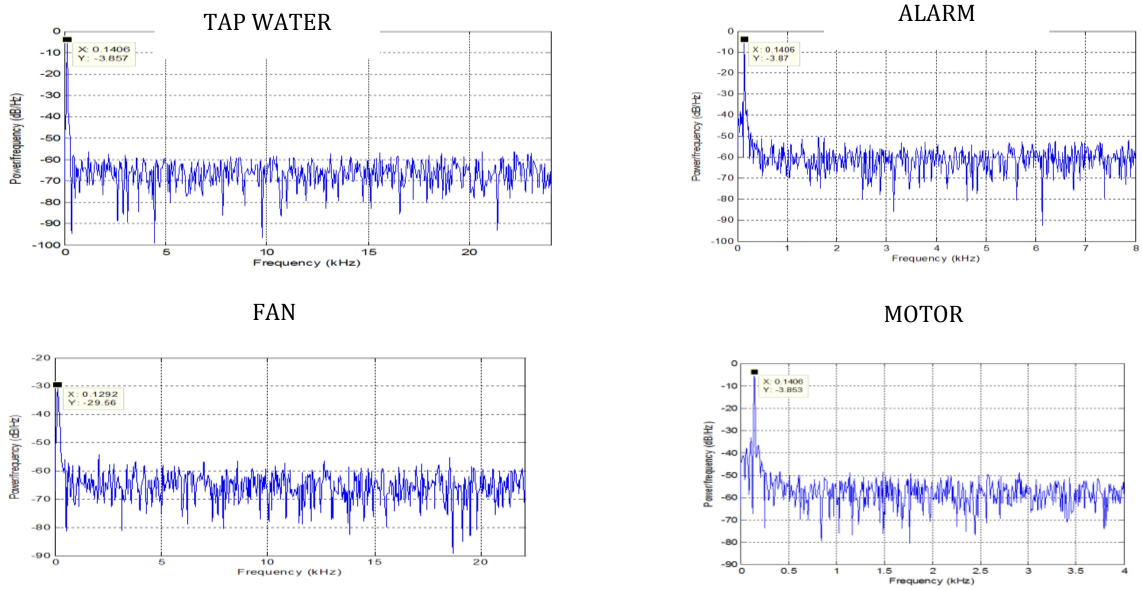


Fig6: Power Spectral Density for Different Electrical Machine's Sounds

Table 2. Power Spectrum Values For Different Audio Signals

Frequency	0.1406	0.1292	0.1406	0.1406
Tap water sounds	-3.868	-29.56	-3.87	-3.853
Alarm sounds	-3.869	-29.8	-3.876	-3.847
Fan sounds	-3.855	-29.99	-3.871	-3.873
Motor sounds	-3.858	-29.79	-3.87	-3.868

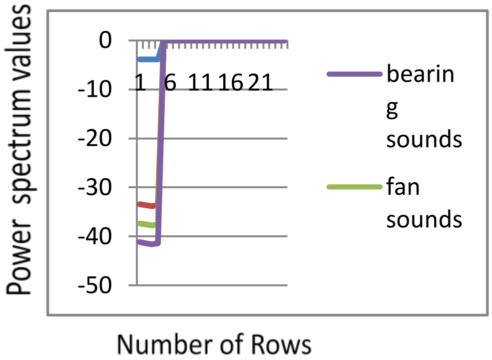


Fig7:Power Spectrum Comparison

3.2 Linear Predictive Coding Results

In this simulation, the audio signal is divided into frames of size 20 ms (160 samples), with an overlap of 10 ms (80 samples). Each frame is windowed using a Hamming window. Eleventh-order autocorrelation coefficients are found, and then the reflection coefficients are calculated from the autocorrelation coefficients using the Levinson-Durbin algorithm. The original audio signal is passed through an analysis filter, which is an all-zero filter with coefficients as the reflection coefficients obtained above. The output of the filter is the residual signal. This residual signal is passed through a synthesis filter which is the inverse of the analysis filter. The output of the synthesis filter is the original signal.

3.2.1 LPC Spectrum for different Alarm sounds

The LPC method uses past samples in each trajectory to predict the best match in the current frame and can interpolate missing peaks and LPC Spectrum values are characterised the different audio signals are shown in fig8 and the comparison model is shown in fig9.

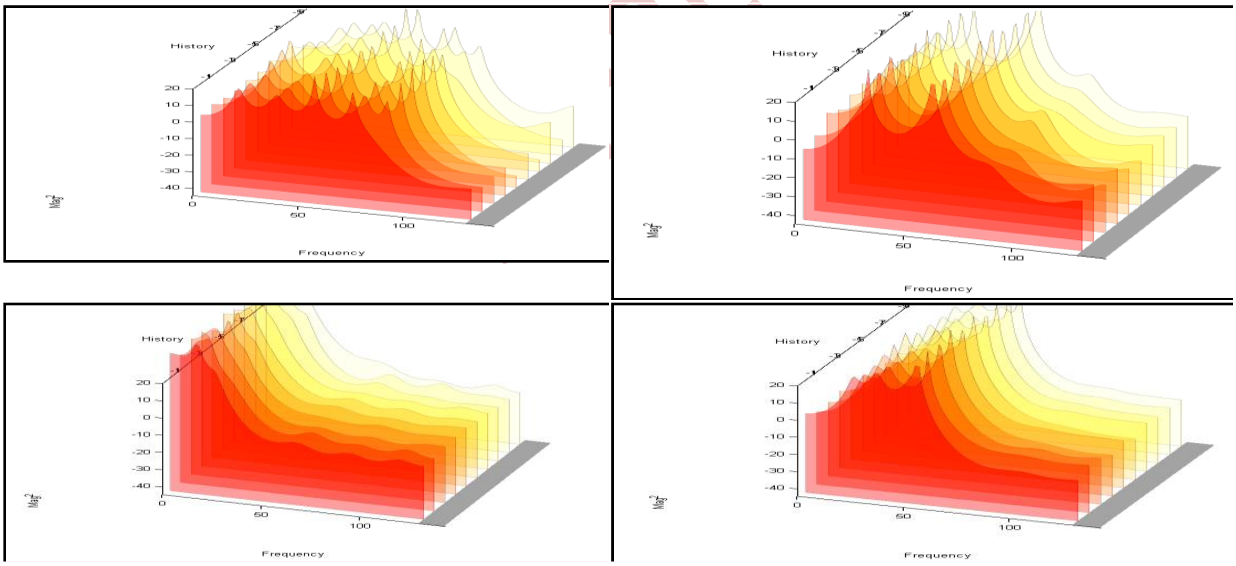


Fig8:LPC Spectrum for Alarm's Sounds

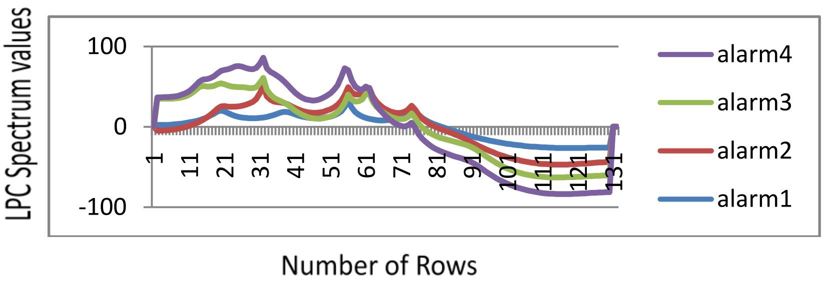


Fig9:LPC Spectrum Comparison between Alarm's Sounds

3.2.2 LPC Spectrum for different Fan sounds

The following LPC spectrum produced the best sample and smoothing sample of the audio signals in fig 10 and comparator model in shown in fig 11.

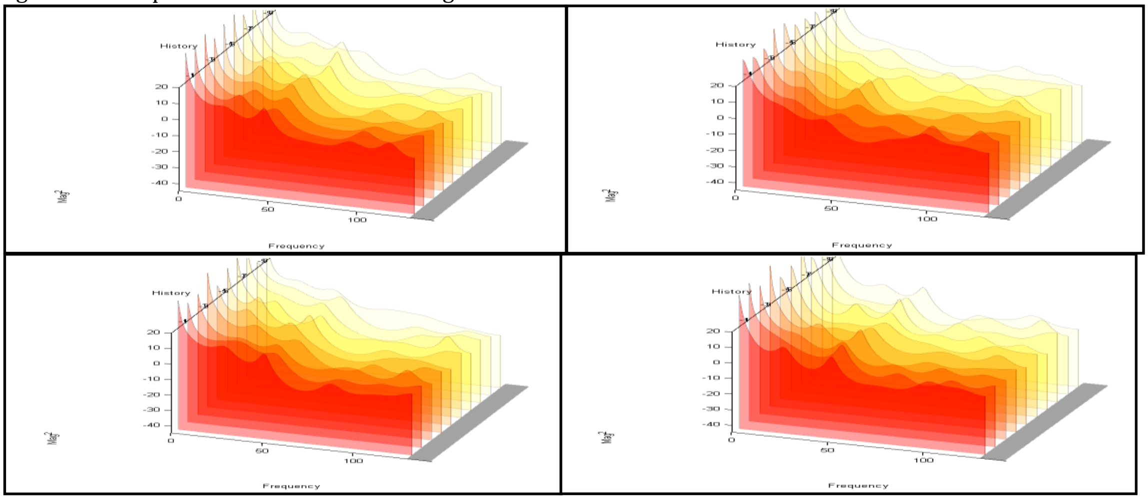


Fig10:LPC Spectrum for Fan Sounds

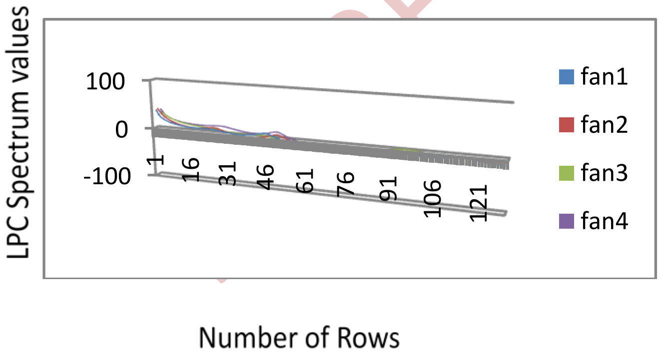


Fig11:LPC Spectrum Comparison between Fan Sounds

3.2.3 LPC Spectrum for Different Tap Water Sounds

The LPC envelope signals are shown in fig12 and comparison model in fig13.

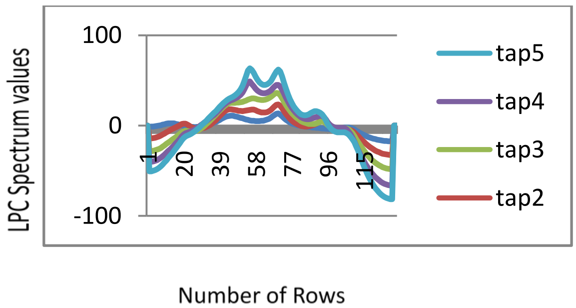


Fig 12: LPC Spectrum Comparison betweenTap Water Sounds

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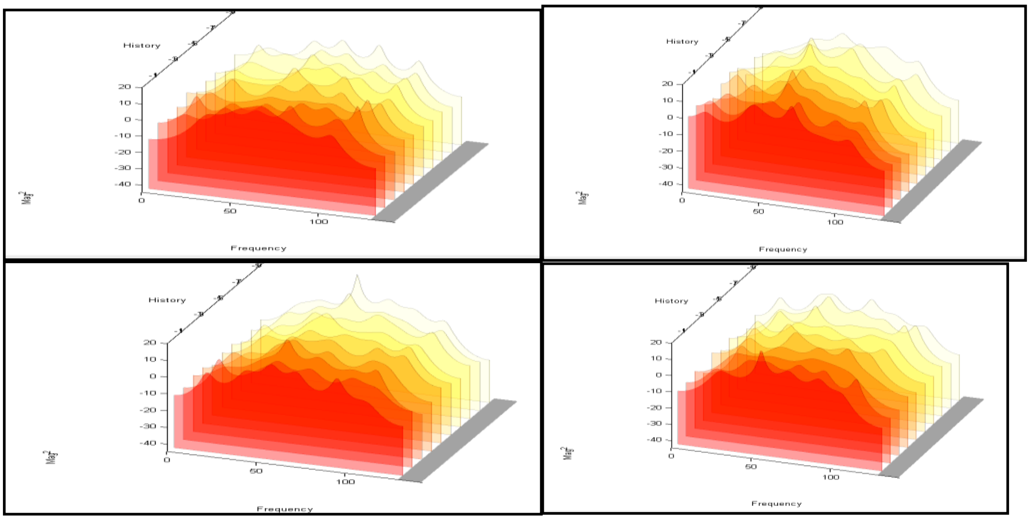


Fig 13: LPC Spectrum for Tap Water Sounds

3.2.3 LPC Spectrum for Different Motor Sounds

The LPC spectrum model and comparison model are shown in fig 14 and 15.

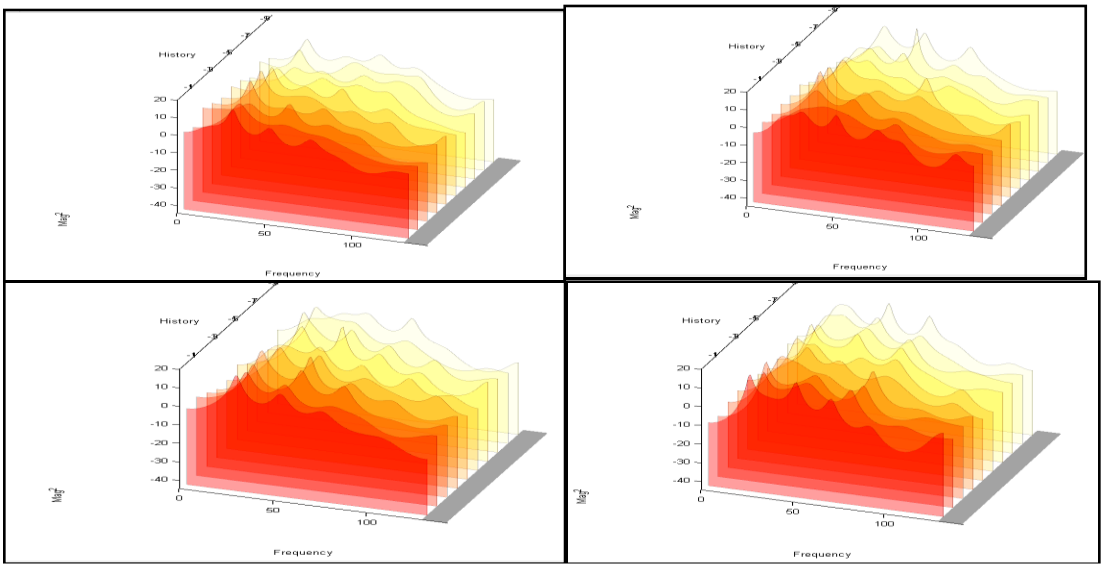
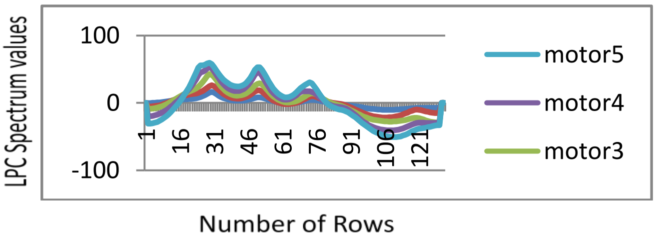


Fig14:LPC Spectrum for Motor Sounds



0Fig15:LPC Spectrum Comparison between Motor Sounds

From these above LPC spectrum and comparison modelling number of audio signal of the same type electrical machine will provide the similarly same results but it is varied compare with another type of audio signal of electrical machines. From these characteristic it is easily identified the input audio signal. These spectrum values are applied to the input signal of HMM model.

3.3 MFCC RESULTS

MFCC produces the 13 cepstral coefficient values these data's are applied to the input signal of HMM model shown in fig 16.

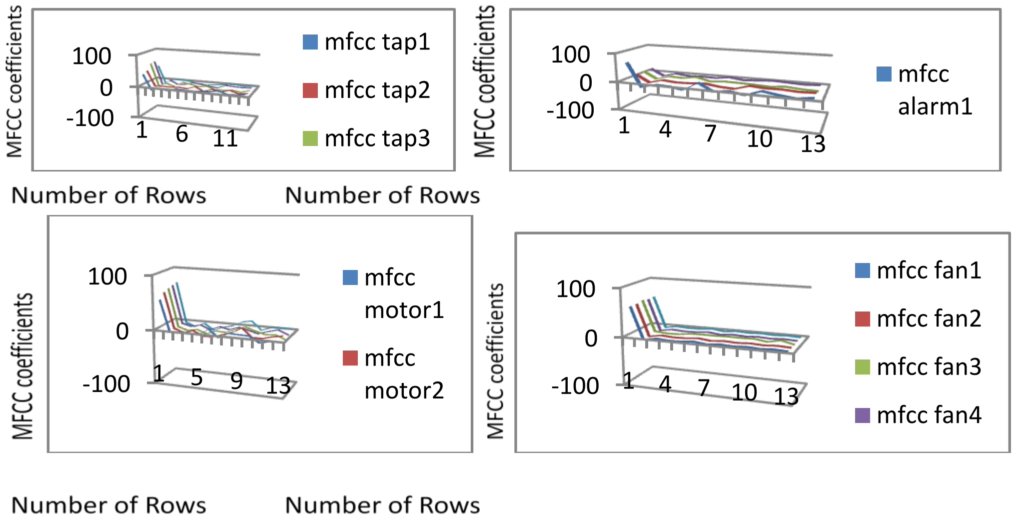


Fig16: 13 MFCC coefficients for different audio signal

3.4 System Identification Model

The system identification model is created by using Hidden Markov Model simulation in table 1 and table 2. These models generate the Log Likelihood value, mean vector and covariance matrix, based on these values to create the database model and then the new input audio signal is compared with the database model and it will generate the particular voltage depending upon the input audio signal as shown in fig17 and fig 18.

Table 3. Hmm Values for MFCC and LPCModeling

HMM values	Tap water	Alarm	Motor	Fan
MFCC	-49.805 124.5163 2.3258	-57.6481 416.1544 1.4314	-53.9868 236.9329 3.5986	-54.9205 273.5342 4.104
LPC	-9.3423 0.2464 1.1853	-6.2773 0.1538 0.9072	-2.5883 0.0872 0.0301	-4.5936 0.1187 0.0262

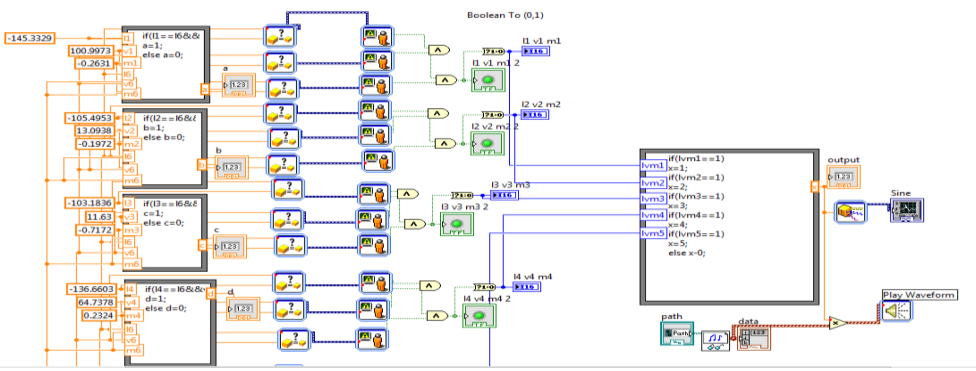


Fig17:System Identification Using HMM Values

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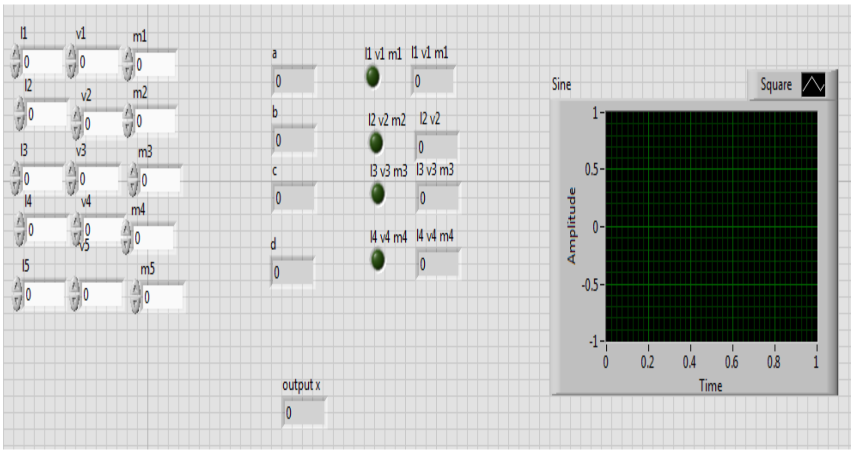
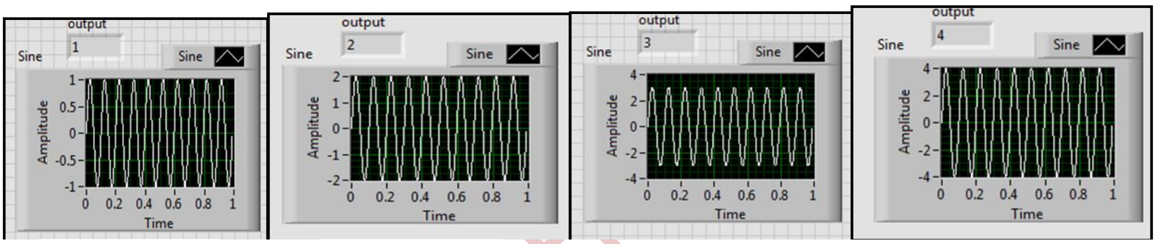


Fig18:Front Panel of System Identification Model

The input signal is matched with the database signals namely alarm sounds, tap water sounds, motor sounds, fan sounds it will execute the following voltage depending upon the audio input signal in fig19.



Alarm Tap water Motor Fan

Fig19:Generating Voltage of Different Audio Signal

By using these HMM values the System Identification Model is created. This model is mainly used for Environmental sound analyses, Electrical Machine's sound analyses, Speech (or) Speaker Identification and Security purpose. Because this Security system will generate the particular response to the user or owner when the system got undefined input audio signal and also the unsafe sound so that the User is easily move to saver zone from critical environment.

4. CONCLUSION

To develop an algorithm for system identification based on audio signal processing, so as to recognize the type of sound generation system, its characteristics and performance. The method is to be analyse during its real time an operation like for example system recognition in the presence of noise. Further the experimental verification of sound recognition based process control is to be done. To identify system based on the following steps

- System identification based on the data base of sound signals.
- Find the working aspect of system using feature extraction.
- Develop a security system based on hidden markov model pattern recognition. So as to operate a system controller like a motor, actuator or switching device on event of uniquely identified sounds.
- Comparing the performance characteristic between LPC and MFCC modelling is shown in fig20.
- Power Spectral Density is plotted for extracting the features of audio signal.

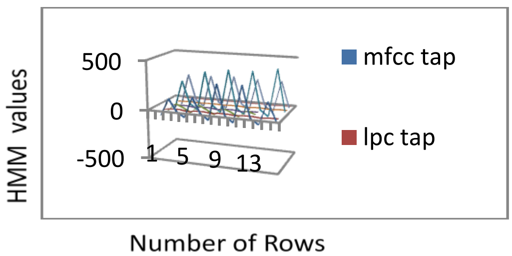


Fig20:Comparison Modelling between MFCC and LPC OfHMM Values

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