Heaven's Light is our Guide

Rajshahi University of Engineering and Technology(Ruet),Rajshahi.

Department of CSE.

Report On Digital Signal Processing

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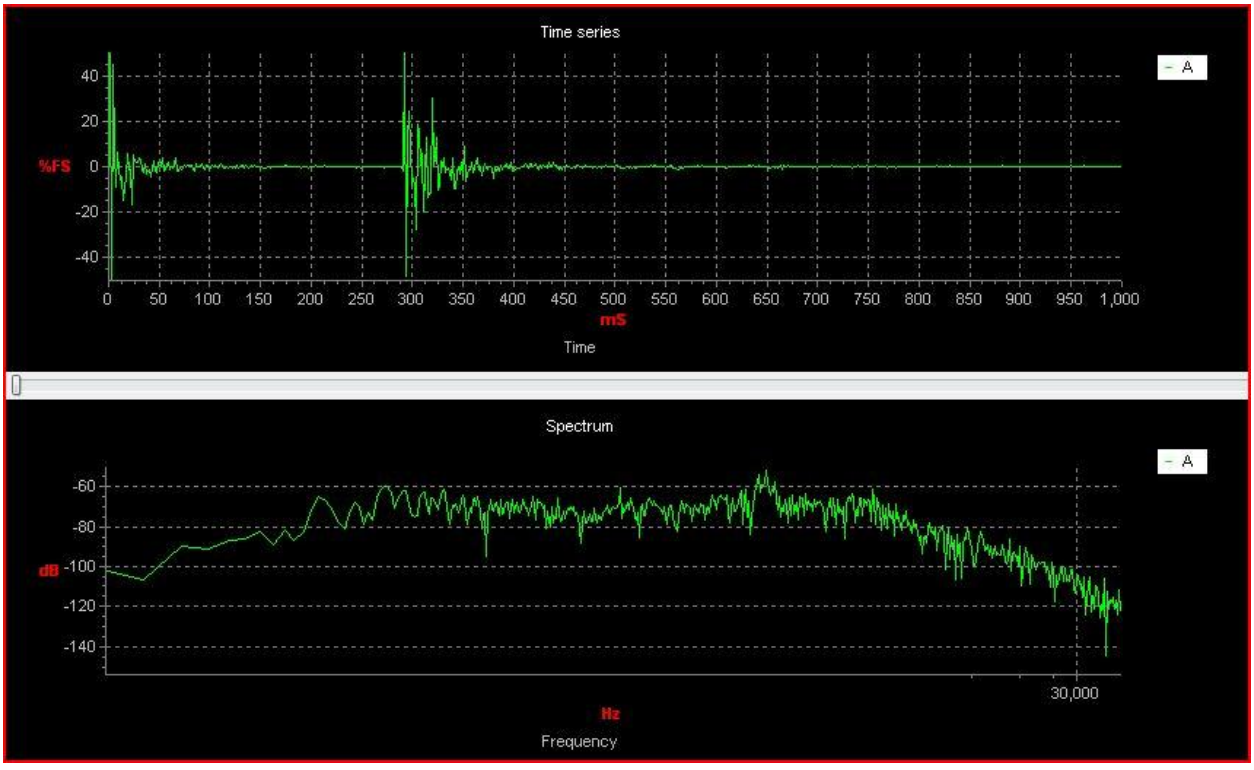
Differentiate between clapping and talking

Take a look at a clap signal and a normal talking signal on the scope. Probably the biggest difference will be the sudden spike from the clap. There is probably a frequency content difference too, but I suspect it will be easier to detect a clap in the time domain.

One way to test this is to record a few samples of the signals you want to detect and reject, then work up a algorithm on the host that scans the WAV files and makes a decision. Once you have that figured out, you can code it in a small DSP, like a Microchip dsPIC.

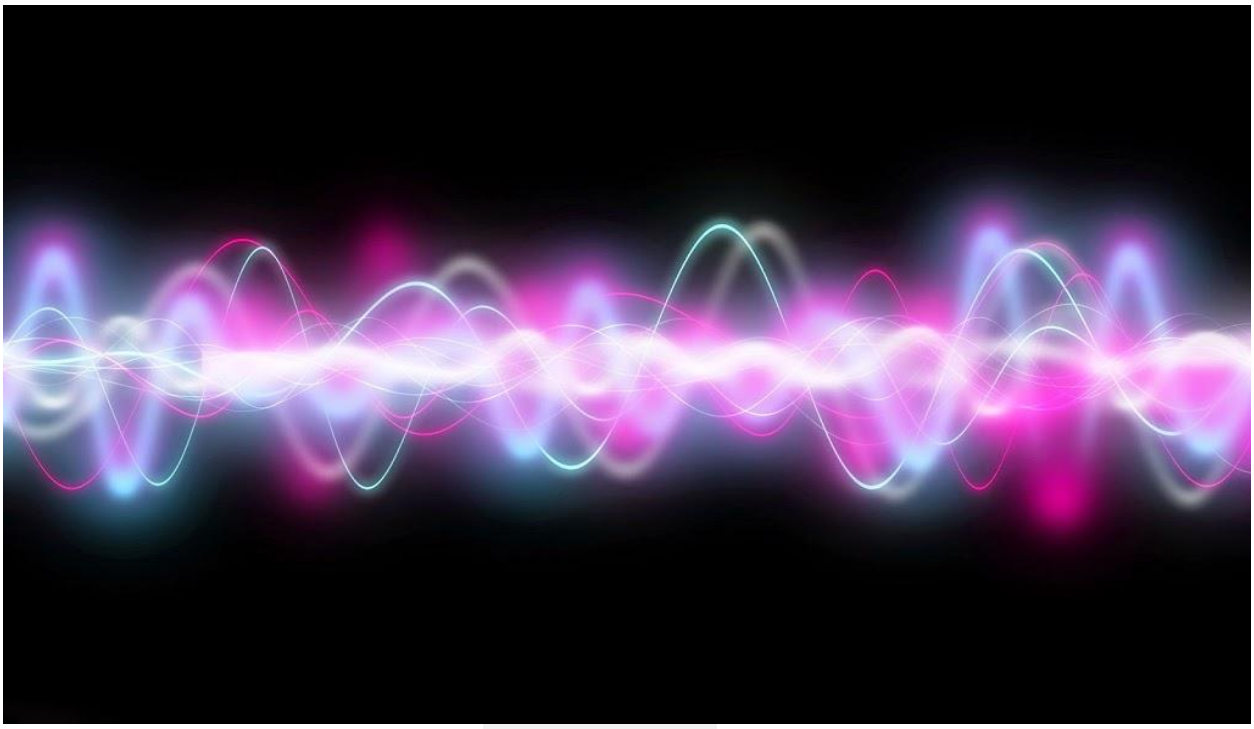
A hand clap also happens quickly, where voice goes on and on (and on and on and on :).



To build something that can distinguish between a clap and a loud voice then you would start by taking the audio and breaking it up into three or more frequency bands. Let's say <200 Hz, 400Hz to 8 KHz, and >13 KHz.

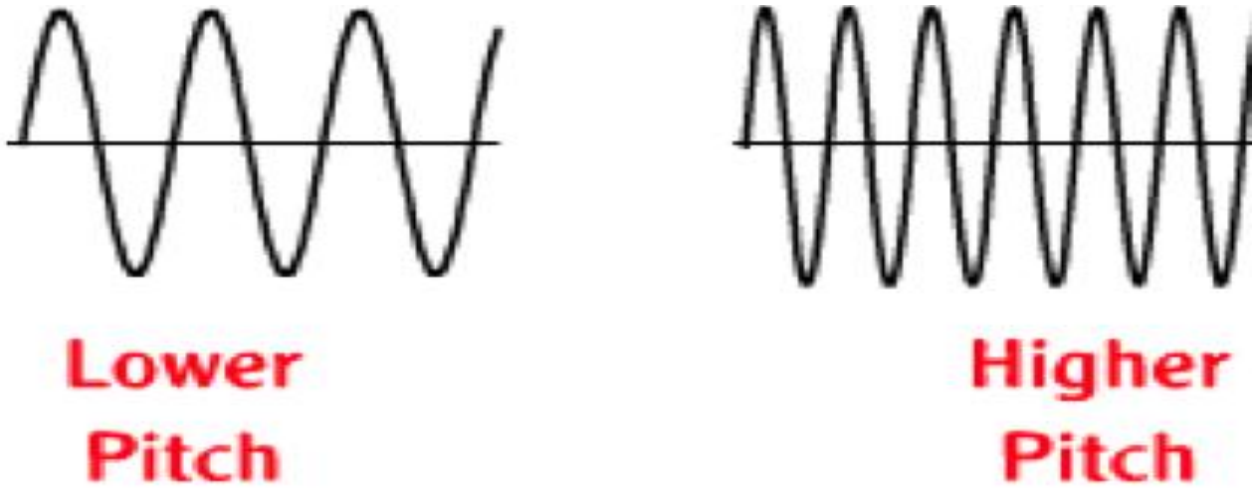
You would then make a detector for each band which would detect peaks greater than some threshold, but not for more than about 200 ms. If you get a short peak on all three bands then you have detected a clap. If you don't get all three bands, or it is greater than 200 ms, then you have just loud voice.

How can the human ear differentiate between sounds?



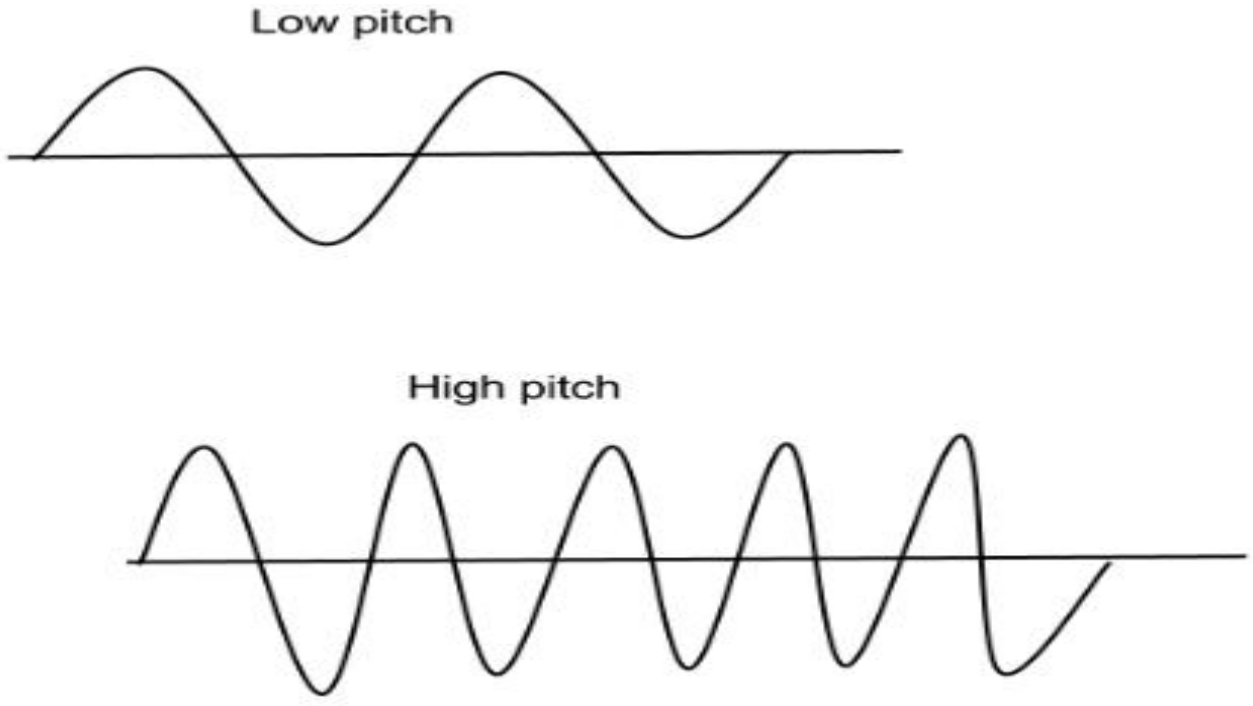
The sound waves

1. The sound pitch: It is very important to know that the human ear differentiate between *the sounds* that reach it through the different factors which are the sound pitch , the sound intensity and the sound quality .



The sound is described as high pitched or low pitched sound .

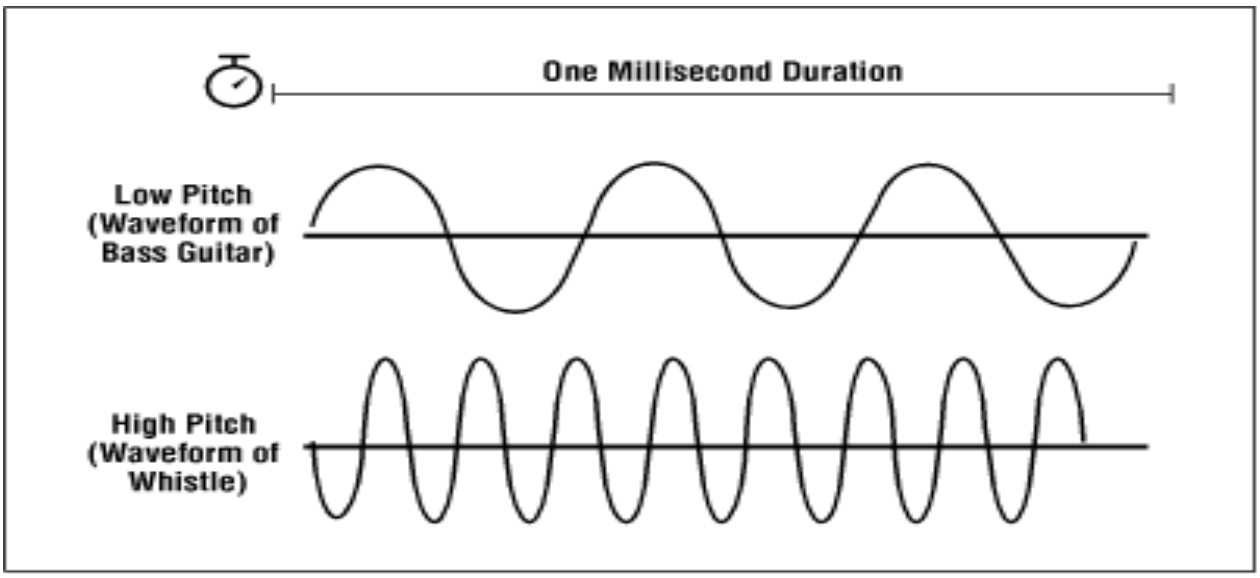
You should know that the sound pitch is a property by which the ear can distinguish between the rough and the sharp voices .
You know that *the sound* is described as high pitched or low pitched , where the high pitched sound is sharp (soft) , And the low pitched sound is rough (hard) .



The sound pitch

You noticed that the voice of the women is high pitched as it is sharp . And the voice of the men is low pitched as it is rough .

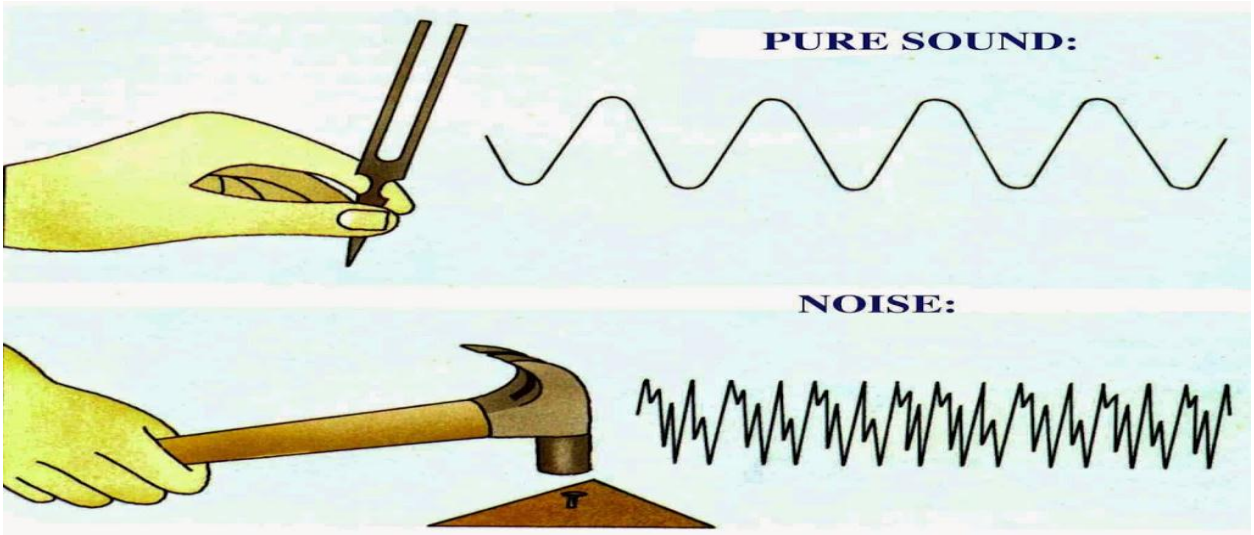
When the sharpness of the voices increases , the level of the voice (the sound pitch) gets higher .



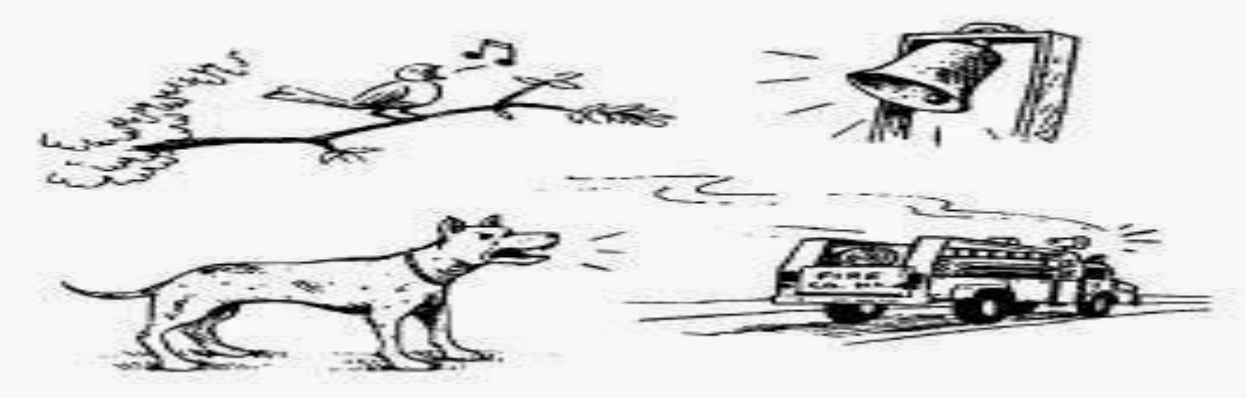
Low pitch sound of the guitar and the high pitch sound of whistle .

The sound pitch depends on the frequency of the sound source , And the sound pitch increases by increasing the frequency and vice versa .

2. *The sound intensity*:



It is very important to know that *the sound intensity* is the property by which the ear can distinguish between the sounds either strong or weak .



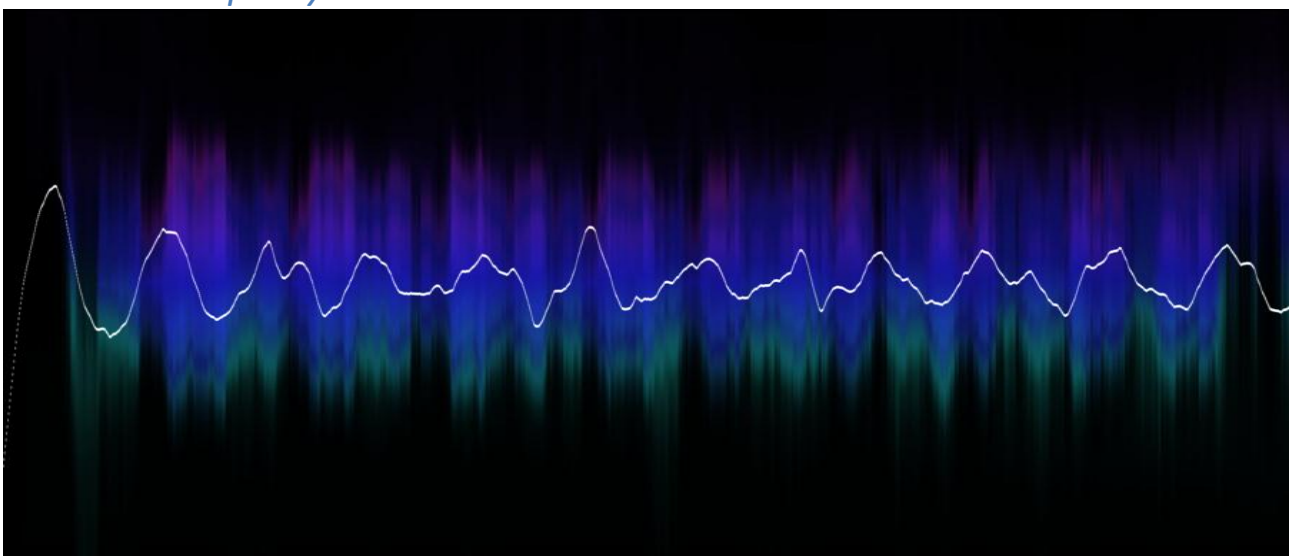
Every sound around us has a level of sound intensity .

You notice that the shouting is stronger than the whispering , And the drum produces strong sound when it is beaten strongly , and it produces weak sound when it is beaten softly .

The level of the sound intensity changes from one person to another

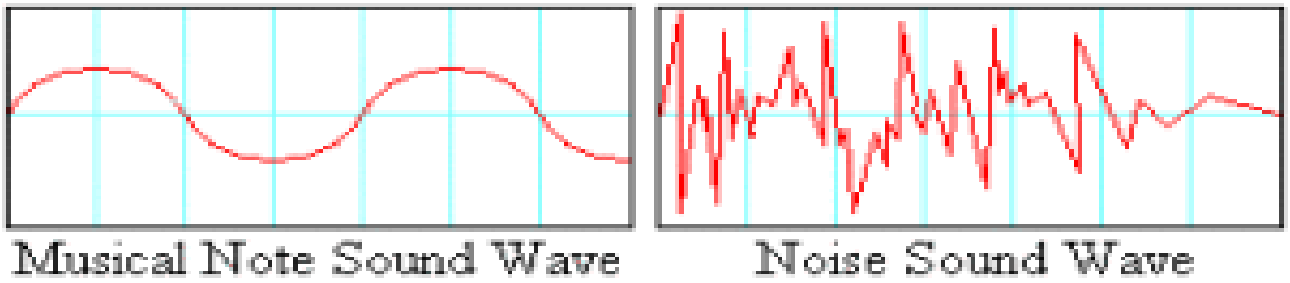
The factors affecting the sound intensity: You should know that the sound intensity at a point depends on the distance between the ear , and the sound source .
It depends on the amplitude of the vibration of the sound source .
It depends on the direction of the wind , And the area of the vibrating surface .
You should know that it depends on the density of the medium through which the sound travels .

3. *The sound quality:*



It is very important to know that the sound quality (type)is the property by which the human ear can distinguish between the different sounds according to the nature of the source even if they are equal in the intensity and the pitch .

The harmonic tones :



The human can distinguishes between the sounds from the different sources .

You should know that *the harmonic tones* are tones that accompany the fundamental tone , But they are lower in the intensity and higher in the pitch , and differ from one instrument to another .
You should know that the human ear distinguishes between the sounds from the different sources even if they are equal in intensity and the pitch due to the harmonic tones that associate the fundamental tone of the source of the sound and are lower in intensity and higher in the pitch .

Identification of Human Voice in Noisy Signals

Abstract: A large amount of machine learning research has been dedicated to understanding human speech, but the ability to identify human speech in the first place can be useful as well. In this paper, an algorithm is described that can identify the presence of a human voice in an audio signal. An investigation into the most relevant features for this process is included in the description. The resultant algorithm applies a Support Vector Machine to the audio features to classify the signal with 90.5% accuracy. The algorithm then filters the classifications to successfully classify the entire audio file correctly.

1. Introduction: The human auditory system is particularly attuned to differentiating human speech from other sounds. The goal of this project is to write an algorithm that can perform live detection of human speech even when partially masked by environmental noise. One envisioned application for such a method is in disaster situations that span a large area or an area that human rescuers cannot enter, robotic “listeners” can be deployed instead and can report if they pick up the voice of survivors in their area. Another application would be for mobile phones that can change their behavior (for example if they ring or vibrate) depending on if they detect the user to be in the middle of a conversation or in a lecture. In the past, machine-learning research has been focused on “speech recognition”, defined as the ability to interpret human speech. Ironically, not as much attention has been paid to the recognition of speech itself versus other forms of noise. For classic speech-recognition there are a variety of features that are used to remove differences between an individual’s tone, accent, and other vocal traits. These features effectively produce a signature of human voice regardless of the speaker. The approach of this paper is to utilize a combination of the features developed for classic

speech recognition algorithms for the more fundamental identification of the presence of speech problem.

2. Dataset: For this project we compiled a unique dataset. We used single voice, single source recordings of people reading poetry found on www.LibriVox.org as our human voice training and testing data. For our noise data we selected an array of noise recordings found in everyday environments from www.SoundJay.com. The types of environmental noise include industrial noise, nature sounds, and household noises. In total, the dataset contained about 4 hours of recorded sounds, approximately split between human and environmental recordings.

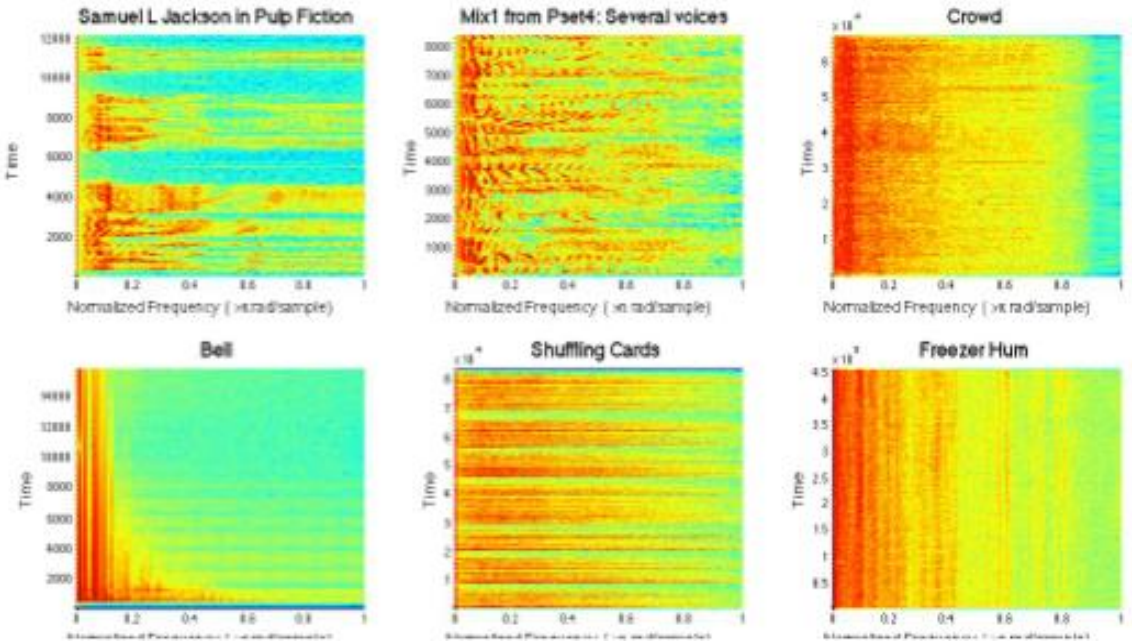


Figure 1: Sample short-time power spectra for different audio signals. There is a clear difference between the spectra of a single human voice and that of Freezer Hum

3. Methods: The development of the algorithm progressed on two main fronts: the features particular to human speech and a classification algorithm that can identify the audio stream in real time with reasonably high accuracy. The dataset audio files were divided up between those that contained a single human voice and those that contained environmental noise. A MATLAB script was created to automatically process the .wav files, record the files' apriori classification, and extract the features.

3.1 Features: The algorithm employs two classes of spectrum-derived features of the audio file. To extract these two sets of features, we used algorithms available in Reference 2. The first class of features is compiled

by comparing the short-time spectra after compressing them in a manner that re-bins and rescales the spectrogram to better mimic how humans perceive sound. The Mel-scale is one such scale; integrating the power spectrum against the bank of filters generates these features. The filters used in the Mel-scale are illustrated below and were designed so that they are perceived as “equally-spaced” in frequency based on human testing. Taking the inverse Fourier transform after this mapping picks out harmonics of voiced signals and generates the Mel Frequency Cepstral Coefficients (MFCC). As noticeable in Figure 1, the covarying harmonics clearly are a unique feature of the spectra. In taking the Fourier transform of the power spectra in this fashion it is hoped that the fundamental frequency of voice box-or sound source might be identified and used as a feature. However, this technique clearly cannot capture all harmonics, as only those that are equally spaced in the Mel scale will be detected, and most sound sources only follow that pattern approximately. Furthermore, harmonics are not always resolvable within the spectrograms.

Voice signals are temporally correlated over short times. Voice recognition algorithms tend to approach the problem by using the “Source-Filter Model” This assumes that voiced sound is comprised of a signal that contains the content of the speech, but then it is filtered as it passes through the vocal tract of the speaker. While the source signal for any given word should be identical regardless of who is saying it, within the model, it is the filter that is unique to every speaker. These filters result in different spectrograms for different people saying the same thing. Most voice-recognition algorithms use a variety of heuristics to re-bin, filter, smooth or rescale any given spectra, so that the effects of different filters are not present in the processed signal. RASTA filtering is another common processing step that smooths noisy spectral features. Machine-learning performed on the processes signal will consequently only be sensitive to the information present in the “source,” and will be able to distinguish between spoken words and other sounds. Perceptual Linear Prediction (PLP) is one technique for extracting features from this processed signal and constitutes the second class of features we examined. In the time-domain, the linear model below is fitted to the processed signal and the ‘a’ coefficients are extracted.

$$x_n = \sum_{k=1} a_k x_{n-k} \cdot C_j = \sum_{k=1} a_k C_{j-k}$$

The fit to the model that optimizes the squared error between x and the signal, yields the equation above for a, expressed in terms of autocorrelation functions, C, which are easily recovered from the Fourier Transform of the processed spectrum.

3.2 Classification: To classify our data we sought an algorithm that will run fast enough to allow for live classification of audio signals. We found that a support vector machine (SVM) with a linear kernel achieved high accuracy as well speed. Our SVM is optimized by L2 regularized norm. In addition, we apply a low pass filter to prevent the output from tracking the misclassification error.

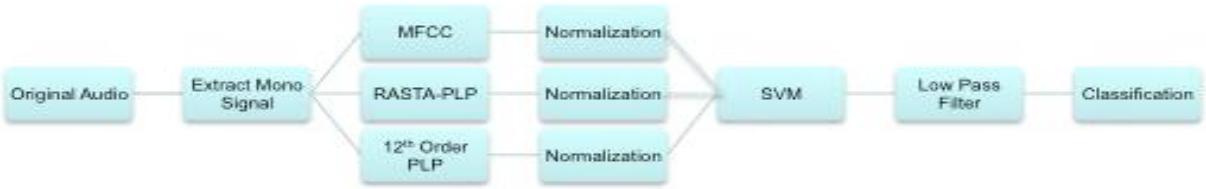


Figure 2: Diagram of Algorithm Scheme

4 Results: A program was developed in MATLAB to apply the algorithm described above to our dataset. The program allows the user to select the percentage of the audio files devoted to training the algorithm and uses the remaining audio to test the classification accuracy of the algorithm.

A

ACTUAL CLASS	PREDICTED CLASS: Noise	PREDICTED CLASS: Human
Noise	90.4%	9.6%
Human	9.8%	90.2%

B

Features	Accuracy (%)
MFCC	69.06
RASTA-PLP	71.09
PLP- 12th order	80.69
ALL	90.52

Figure 3: A. Confusion matrix of the algorithm when using all of the features of the dataset. Note that the algorithm does about as well for classifying both positive and negative data. B. Classification accuracy of the algorithm using various subsets of features. Values were taken when SVM was trained on 85% of our positive and negative data and tested on the remaining portion of data.

4.1 SVM Classification:

The SVM step was quite successful at classifying the files in our dataset. As seen in Figure 3A, the percentage of false-negatives and false-positives are about the same. The different feature sets that were employed each produced different levels of accuracy when the SVM was trained off only that feature. This was likely due to the fact that each of the features is designed to pick up on a different aspect of human speech. For example, the RASTA-PLP is very good at picking up the onset of syllables and words, but the MFCC is about the same A B across a whole syllable. The combination of these features was able to produce a much higher accuracy than their individual applications [Figure 3B].

4.2 Filtering: The high accuracy of the SVM was over the entire file, but there is still an error of ~10% that causes the classification of a live audio signal to appear choppy. These misclassifications happen most often by the natural breaks in human speech, between syllables and words. By applying a filter, the SVM removes these brief misclassifications and achieves a much higher accuracy for the incoming audio stream as seen in Figure 4.

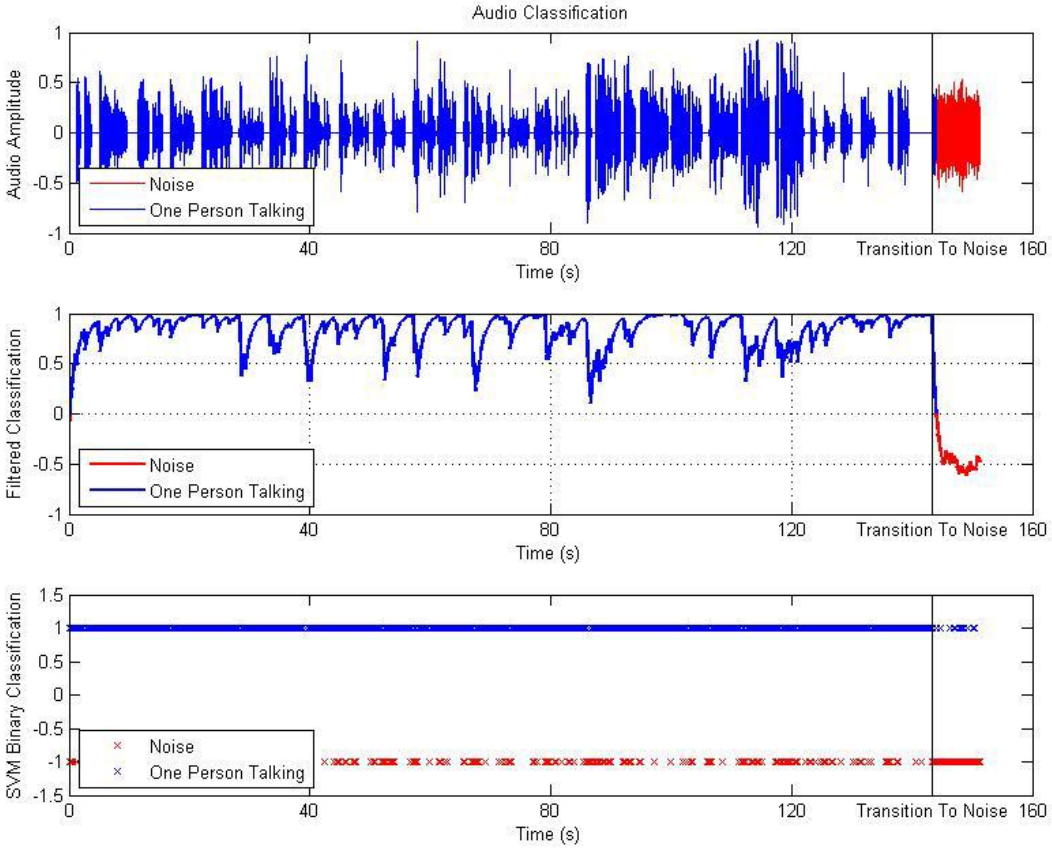


Figure 4: Classification of streaming audio signal with filtering. A. The incoming audio signal starts with a single person talking and transitions to the sound of freezer hum at ~140 seconds. B. Decision values of algorithm after filtering. C. Raw SVM classifications before filtering

4.3 Classification in Noisy Signals: After training the algorithm on clean recordings of human speakers and environmental sounds, the algorithm was tested on a mixture of these signals. To accomplish this, the volume of a particular environmental noise was held constant and the volume of a speaker was adjusted from zero to one hundred percent of their full volume.

When the speaker is at one hundred percent, the two audio signals are about the same volume. The algorithm's accuracy at identifying the speaker's presence was recorded [Figure 5]. When the speaker represents over 20% of the sound in the audio file, the algorithm classifies a majority of the signal as containing a human voice. This result suggests that the algorithm should prove useful to identify human voices in the noisy environments of disaster situations or our everyday lives.

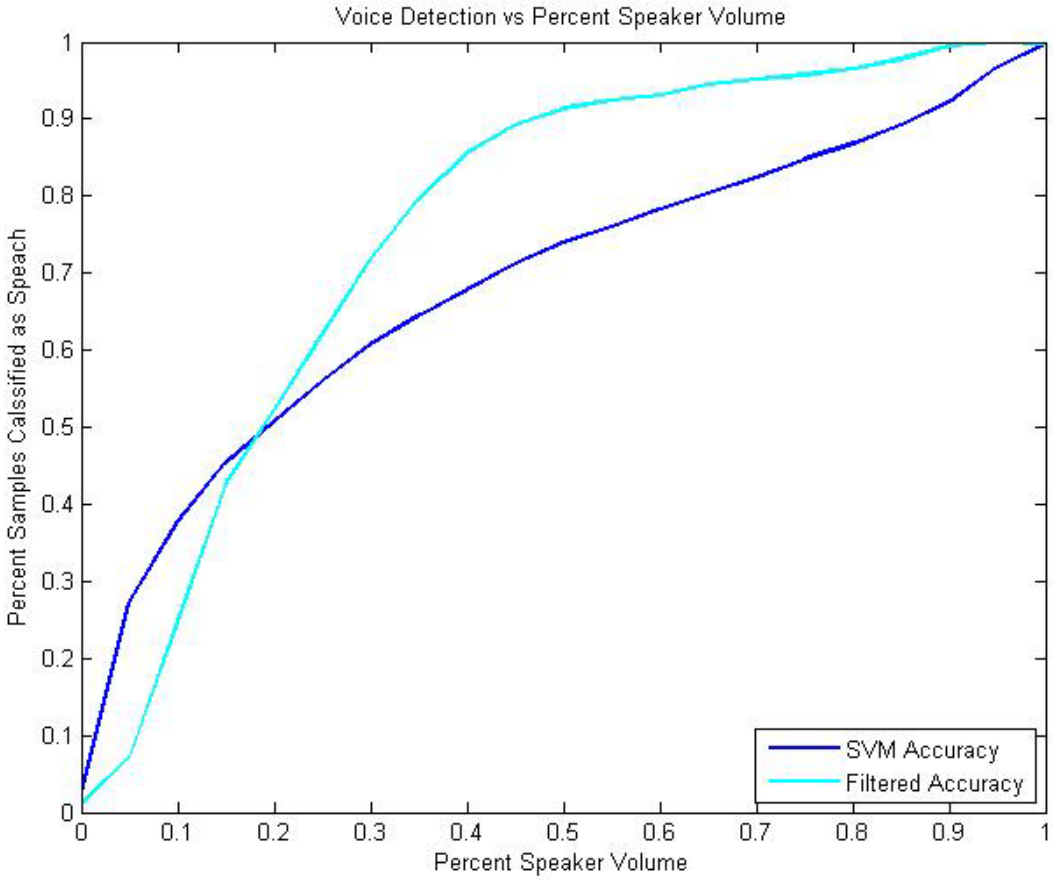


Figure 5: Example relationship between the amount of environmental noise in an audio file and the ability to identify human voice. When the voice is at ~20% the algorithm successfully picks up the voice as the dominant classification.

5. Conclusion and Future Work: This paper presented a strong start to the development of an algorithm to identify human voice in noise environments. The algorithm presented here is currently fast enough to process an incoming signal, but it may prove useful to develop a less computationally intensive set of features. In addition there may be certain sources of environmental noise that were not considered but could be sufficiently similar to the human voice to cause misclassification such as animal noises. This possibility can be tested by compiling an even larger dataset of environmental noise for training and testing.

Another possible extension of the work we have done is counting the number of unique speakers in an audio sample. The features we used, in particular the PLP, are explicitly designed to remove essential differences of the signals of two people saying the same thing. It is not surprising, that when training and testing the SVM off sets of multiple people talking and one person talking, it has a hard time distinguishing between the two categories. Likewise, the SVM cannot distinguish between a crowd of people and a single speaker. Simple tests of nonlinear SVMs have not been effective, though further exploration might prove fruitful. This suggests that the features we chose are not suited

for this application. Finer details of the spectrogram might be used instead to count the number of people talking. In particular the correlations between the time-dependence of the harmonics of the voice spectrograms might be a particularly useful set of features.