Speech Recognition System using the DTW Method

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***Abstract*—Speech recognition is a fundamental component of modern human-computer interaction systems. Dynamic Time Warping (DTW) has emerged as a powerful technique for speech recognition, especially in scenarios where traditional methods like Hidden Markov Models (HMMs) face challenges such as variability in speech patterns and non-linear temporal alignments. This paper presents a speech recognition system based on DTW, focusing on its effectiveness in handling diverse speech inputs. The system incorporates pre-processing techniques for feature extraction, such as Mel Frequency Cepstral Coefficients (MFCCs), to represent speech signals effectively. DTW is then applied on the test dataset to compare these feature representations with reference templates, enabling robust recognition even in noisy environments or with limited training data. The scalability and adaptability of DTW make it a promising approach for real-world applications requiring accurate and robust speech recognition capabilities.**

***Index Terms*—Feature Extraction, Feature Matching, Mel Frequency Cepstral Coefficients (MFCC), Dynamic Time Warping (DTW), Discrete Cosine Transform (DCT)**

I. Introduction

Speech recognition plays a pivotal role in various applications, from virtual assistants to hands-free control systems. Traditional approaches to speech recognition, such as Hidden Markov Models (HMMs), have been widely used but often encounter challenges with variability in speech patterns and non-linear temporal alignments. Dynamic Time Warping (DTW) has emerged as a robust alternative, particularly effective in scenarios where precise alignment of speech sequences is crucial. By allowing flexible matching of temporal sequences, DTW can accommodate variations in speech speed and timing, making it suitable for real-world applications with diverse speech inputs.

In this paper, we present a speech recognition system leveraging DTW as the core technique. The system is designed to handle a wide range of speech inputs while maintaining high accuracy and reliability. Key components of the system include pre-processing techniques like Mel Frequency Cepstral Coefficients (MFCCs) for feature extraction, which provide a compact yet informative representation of speech signals. DTW is then applied to compare these feature vectors with reference templates, enabling robust recognition even in noisy environments or with limited training data.

The rest of this paper is organized as follows: Section II details the implementation of our DTW-based speech recognition system, including data preprocessing, feature extraction, and the DTW algorithm itself. Section III presents experimental results and performance evaluations on the dataset, demonstrating the efficacy of our approach.

II. Implementation

A. Dataset

The dataset comprises forty recordings, four recordings of each digit from 0-9. For training and testing purposes, we partitioned the dataset into standard training and testing datasets, with the training dataset consisting of thirty recordings and the remaining ten going to the testing dataset. The goal is to develop an automatic speech recognition system capable of accurately identifying digits irrespective of speech flow, loudness, intonation and intensity of overtones.

B. Data pre-processing

Before training the model, other tasks such as data loading and preprocessing tasks, including reading data from WAV files and dividing the data into training test sets were handled.

All speech signals were normalized to have zero mean and unit variance. This step ensured consistent signal amplitude across recordings, reducing the impact of amplitude variations on feature extraction and recognition.

The normalized speech signals were segmented into frames using a fixed-length windowing technique. Each frame typically spanned 20-30 milliseconds, with a 10-millisecond overlap between consecutive frames. This frame segmentation process facilitated the extraction of time-varying features from the speech signals.

Mel Frequency Cepstral Coefficients (MFCCs) were extracted from each frame to capture spectral characteristics and temporal dynamics of the speech signals. The MFCCs were computed using a standard feature extraction pipeline, including the application of a Mel filterbank, logarithmic scaling, Discrete Cosine Transform, and liftering to emphasize relevant frequency components.

The extracted MFCC features were normalized to have zero mean and unit variance across frames within each utterance. This normalization step enhanced the robustness of the feature representation by mitigating variations in speech intensity and loudness.

Categorical classification accuracy was employed as the performance metric for evaluating the model.

C. Methodology

Reference templates for each digit are constructed using a training dataset comprising examples of each digit spoken by multiple speakers. These templates capture the expected patterns for each digit, accounting for variations in speech due to different speakers, speaking rates, and accents.

DTW is a dynamic programming algorithm that measures the similarity between two sequences with varying lengths and alignments. It finds the optimal alignment between a query sequence (input speech signal) and a reference sequence (digit template) by minimizing the total distance or cost between corresponding elements. The algorithm works by creating a matrix where each cell represents the cumulative distance between corresponding elements of the two sequences at that point. The goal is to find the path through this matrix that minimizes the total distance. DTW allows for flexible matching of sequences by considering local alignments and allowing for warping or stretching of the sequences in the time domain. This flexibility is crucial for handling variations in speech timing and duration.

We recognized a spoken digit by preprocessing the input speech signal to extract MFCC feature vectors, computing the DTW distance between the input feature sequence and each reference template (one for each digit), and selecting the digit with the lowest DTW distance as the recognized digit, indicating the closest match between the input speech and the reference templates.

III. Results and Discussions

The performance of the proposed Dynamic Time Warping (DTW)-based digit recognition system was evaluated using a small dataset comprising spoken digits (0-9) across varying conditions.

The system achieved a remarkable accuracy of 100%, indicating perfect recognition of spoken digits across all test samples. Precision, recall, and F1 score values of 1.0 were also obtained for each digit class, demonstrating the system's ability to correctly classify all instances of each digit without any false positives or false negatives.

References

[1] Senin, Pavel. (2009). Dynamic Time Warping Algorithm Review.

[2] Majeed, Sayf & HUSAIN, HAFIZAH & Samad, Salina & Idbeaa, Tarik. (2015). Mel frequency cepstral coefficients (Mfcc) feature extraction enhancement in the application of speech recognition: A comparison study. Journal of Theoretical and Applied Information Technology. 79. 38-56.

[3] Z. K. Abdul and A. K. Al-Talabani, "Mel Frequency Cepstral Coefficient and its Applications: A Review," in IEEE Access, vol. 10, pp. 122136-122158, 2022, doi: 10.1109/ACCESS.2022.3223444.

[4] Bhadragiri Jagan Mohan and Ramesh Babu N., "Speech recognition using MFCC and DTW," 2014 International Conference on Advances in Electrical Engineering (ICAEE), Vellore, India, 2014, pp. 1-4, doi: 10.1109/ICAEE.2014.6838564.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Function to read .wav file

```
import wave
import numpy as np
import pylab as pl

def wavread(filename):
    # Read wav file
    print('Reading WAV file  ',filename,'---\n')
    wavefile = wave.open(filename, 'r')

    #Function to read four types of information from wav files. numframes indicates how many frames were read in total
    nchannels = wavefile.getnchannels()            # Returns number of audio channels (1 for mono, 2 for stereo).
    sample_width = wavefile.getsampwidth()         # Returns sample width in bytes.
    framerate = wavefile.getframerate()            # Returns sampling frequency.
    numframes = wavefile.getnframes()              # Returns number of audio frames.

    #print("channel",nchannels)
    #print("sample_width",sample_width)
    #print("framerate",framerate)
    #print("numframes",numframes)

    str_data = wavefile.readframes(numframes)      # Reads and returns at most n frames of audio, as a bytes object.
    wavefile.close()

    #Convert waveform data to array
    wave_data = np.fromstring(str_data, dtype=np.short)
    #print(len(wave_data))
    time = np.arange(0, numframes) * (1.0 / framerate)
    #print(len(time))

    return wave_data
```

Pre-emphasis

```
def pre_emphasis(signal,coefficient=0.95):
    '''
    Pre-emphasize the signal
    Parameter meaning:-
    signal: original signal
    coefficient: emphasis coefficient, default is 0.95
    '''
    print('Pre emphasis \n')
    return numpy.append(signal[0],signal[1:]-coefficient*signal[:-1])
```

Signal framing and windowing

```
def enframe(signal, nw, inc, winfunc):
    '''
    Convert audio signals into frames.
    Parameter meaning:
    signal:original audio model
    nw: The length of each frame (here refers to the length of the sampling point, that is, the sampling frequency multiplied by the
    inc: interval between adjacent frames (same as defined above)
    '''
    print('Signal framing and windowing \n')
    signal_length=len(signal) #total signal length
    if signal_length<=nw: #If the signal length is less than the length of one frame, the number of frames is defined as 1
        nf=1
    else: #Otherwise, calculate the total length of the frame
        nf=int(np.ceil((1.0*signal_length-nw+inc)/inc))
    pad_length=int((nf-1)*inc+nw) #The total flattened length of all frames added up
    zeros=np.zeros((pad_length-signal_length,)) #Insufficient lengths are padded with 0s, similar to the extended array operation in
    pad_signal=np.concatenate((signal,zeros)) #The padded signal is recorded as pad_signal
    indices=np.tile(np.arange(0,nw),(nf,1))+np.tile(np.arange(0,nf*inc,inc),(nw,1)).T  #It is equivalent to extracting the time poin
    indices=np.array(indices,dtype=np.int32) #Convert indices into matrices
    frames=pad_signal[indices] #Get frame signal
    win=np.tile(winfunc,(nf,1))  #window window function, the default value here is 1
    #print(np.shape(frames*win))
    return frames*win   #Return frame signal matrix
```

```
def sgn(n):                      # Returns the sign of frames, used in ZCR Calculation
    if n>=0:
        return 1
    if n<0:
        return -1

def energy(frames):
    #print(frames)
    frames=frames/np.amax(np.absolute(frames))  # classified as [-1,1]
    nframe=np.shape(frames)[0]                  # Number of frames
    lframe=np.shape(frames)[1]                  # Energy of frames
    energy=np.power(frames,2)                   # Sum energy along each frame
    e=energy.sum(axis=1)
    time = np.arange(0, nframe)
    pl.plot(time,e)
    pl.xlabel("Time")
    pl.ylabel("Energy of signal")
    pl.show()
    return e

def zcr(frames):
    nframe=np.shape(frames)[0]                   # Number of frames
    lframe=np.shape(frames)[1]                   # Length of each frame
    zcr=np.zeros(nframe)                         # Initialize zero crossing rate array
    for i in range(nframe):
        zframe=0
        for j in range(1,lframe):
            zframe=zframe+0.5*(abs(sgn(frames[i,j])-sgn(frames[i,j-1])))
        zcr[i]=zframe/(lframe-1)                 # Compute zero crossing rate for each frame
    time = np.arange(0, nframe)
    pl.plot(time,zcr)
    pl.xlabel("Time")
    pl.ylabel("Zero crossing Rate")
    pl.show()
    return zcr

def vioceextrac(frames):
    print('Extracting active voice \n')
    nframe=np.shape(frames)[0]                    # Number of frames
    lframe=np.shape(frames)[1]
    mh=10                                         # High energy threshold
    ml=2                                          # Low energy threshold
    zs=0.18                                       # Zero crossing rate threshold
    a1=0
    a2=0
    status=0
    count=0                                       # This variable counts the number of consecutive frames with energy levels below mh
    e=energy(frames)                              # Compute energy of frames
    z=zcr(frames)                                 # Compute zero crossing rate of frames
    mh=min(mh,np.amax(e)/4)                       # Adjust high energy threshold
    ml=min(ml,np.amax(e)/8)                       # Adjust low energy threshold
    #print(mh,ml)
    for i in range(nframe):                       # a1, a2, a2t: These variables are used to track the indices of frames where active
        if status==0 and e[i]>mh:
            a1=i
            status=1
        if status==1 and e[i]<mh:
            a2t=i
```

```
            status=2
        if status==2 and e[i]<mh:
            count=count+1
        if status==2 and e[i]>mh:
            count=0
            status=1
        if status==2 and count>30:
            a2=a2t
    #print(a1,a2)
    b1=a1-1                                      # b1, b2: These variables are used to adjust the boundaries of the active voice segm
    b2=a2+1
    while e[b1]>ml:
        b1=b1-1
    while e[b2]>ml:
        b2=b2+1
    #print(b1,b2)
    c1=b1-1                                     # c1, c2: These variables are used to further refine the boundaries of the active voi
    c2=b2+1
    while z[c1]>=(3*zs):                        # status: This variable tracks the current state of processing the frames. It transit
        c1=c1-1
    while z[c2]>=(3*zs):
        c2=c2+1
    #print(c1,c2)
    frames_a=frames[c1:c2,:]
    return(frames_a)                            # Return frames containing active voice segments
```

Feature Extraction (using MFCC)

```
import numpy
import scipy.io.wavfile
from scipy.fftpack import dct

def mfcc(frames,NFFT=512,sample_rate=16000):
    print('Computing MFCC features \n')
    #frame energy spectrum
    mag_frames = numpy.absolute(numpy.fft.rfft(frames, NFFT))  # Magnitude of the FFT
    pow_frames = ((1.0 / NFFT) * ((mag_frames) ** 2))  # Power Spectrum
    energy=numpy.sum(pow_frames,1)  #Sum the energy spectrum of each frame
    energy=numpy.where(energy==0,numpy.finfo(float).eps,energy)  #Adjust the places where the energy is 0 to eps, which facilitates 
    #print(numpy.shape(mag_frames),numpy.shape(pow_frames))
    #filter bank
    nfilt=40

    low_freq_mel = 0
    high_freq_mel = (2595 * numpy.log10(1 + (sample_rate / 2) / 700))  # Convert Hz to Mel
    mel_points = numpy.linspace(low_freq_mel, high_freq_mel, nfilt + 2)  # Equally spaced in Mel scale
    hz_points = (700 * (10**(mel_points / 2595) - 1))  # Convert Mel to Hz
    bin = numpy.floor((NFFT + 1) * hz_points / sample_rate)

    fbank = numpy.zeros((nfilt, int(numpy.floor(NFFT / 2 + 1))))
    for m in range(1, nfilt + 1):
        f_m_minus = int(bin[m - 1])   # left
        f_m = int(bin[m])             # center
        f_m_plus = int(bin[m + 1])    # right

        for k in range(f_m_minus, f_m):
            fbank[m - 1, k] = (k - bin[m - 1]) / (bin[m] - bin[m - 1])
        for k in range(f_m, f_m_plus):
            fbank[m - 1, k] = (bin[m + 1] - k) / (bin[m + 1] - bin[m])
    filter_banks = numpy.dot(pow_frames, fbank.T)
    filter_banks = numpy.where(filter_banks == 0, numpy.finfo(float).eps, filter_banks)  # Numerical Stability
    filter_banks = 20 * numpy.log10(filter_banks)  # dB

    #mfcc
    num_ceps = 13
    appendEnergy=1

    mfcc = dct(filter_banks, type=2, axis=1, norm='ortho')[:, 1 : (num_ceps + 1)] # Keep 2-13
    if appendEnergy:
        mfcc[:,0]=numpy.log(energy)  #Take only 2-13 coefficients and replace the first one with the logarithm of the energy
    #mean-normalized
    mfcc -= (numpy.mean(mfcc, axis=0) + 1e-8)


    return mfcc_delta_delta(mfcc)

def derivate(feat,big_theta=2,cep_num=13):
    '''General transformation formula for calculating first-order coefficients or acceleration coefficients
    Parameter Description:
    feat: MFCC array or first-order coefficient array
    big_theta: the big theta in the formula, the default is 2. This parameter controls the range of the calculation
    '''
    result=numpy.zeros(feat.shape) #result
    denominator=0  #Denominator
    for theta in numpy.linspace(1,big_theta,big_theta):
        denominator=denominator+theta**2
    denominator=denominator*2 #Calculate the value of the denominator
    for row in numpy.linspace(0,feat.shape[0]-1,feat.shape[0]):
        tmp=numpy.zeros((cep_num,))
        numerator=numpy.zeros((cep_num,)) #numerator
        for t in numpy.linspace(1,cep_num,cep_num):
            a=0
            b=0
            s=0
            for theta in numpy.linspace(1,big_theta,big_theta):
                if (t+theta)>cep_num:
                    a=0
                else:
                    a=feat[int(row)][int(t+theta-1)]
                if (t-theta)<1:
                    b=0
                else:
                    b=feat[int(row)][int(t-theta-1)]
                s+=theta*(a-b)
            numerator[int(t-1)]=s
        tmp=numerator*1.0/denominator
        result[int(row)]=tmp
    return result


```

```
def mfcc_delta(feat):
    '''Calculate 13 MFCC+13 first-order differential coefficients
    '''
    result=derivate(feat) #Call the derive function
    result=numpy.concatenate((feat,result),axis=1)
    return result


def mfcc_delta_delta(feat):
    '''Calculate 13 MFCCs + 13 first-order differential coefficients + 13 acceleration coefficients, a total of 39 coefficients
    '''
    result1=derivate(feat)
    result2=derivate(result1)
    result3=numpy.concatenate((feat,result1),axis=1)
    result=numpy.concatenate((result3,result2),axis=1)
    return result
```

DTW Principle

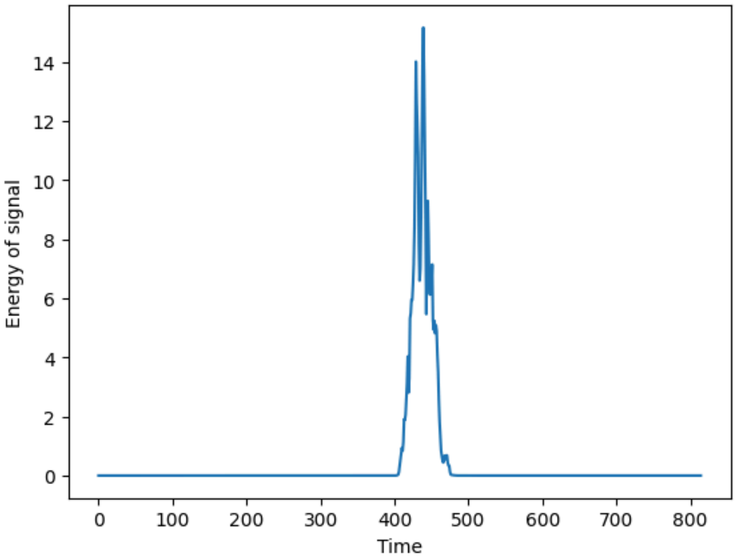
```
import numpy as np

def dist(feat1,feat2):                                                  # Calculates the Euclidean distance between feat1 and fea
    n=np.shape(feat1)[0]
    m=np.shape(feat2)[0]
    d=np.zeros((n,m))
    for i in range(n):
        for j in range(m):
            d[i,j]=np.sqrt(np.sum(np.square(feat1[i,:]-feat2[j,:])))
    return d

def dtw(dist):

    realmax=1.79E+308                                                   # Maximum values of numerical operations
    n=np.shape(dist)[0]
    m=np.shape(dist)[1]                                                 # dimensions of the distance matrix
    D=np.ones((n+1,m+1))*realmax                                        # initializes a matrix D with dimensions (n+1) x (m+1) f:
    D[0,0]=0
    #print(D)                                                        # sets the starting point of the DTW matrix to 0
    for i in range(1,n+1):
        for j in range(1,m+1):
            D[i,j]=dist[i-1,j-1]+min(D[i-1,j],D[i,j-1],D[i-1,j-1])
    return D[n,m]

def score(feat1,feat2):                                                 #   calculates the DTW score (similarity) between two se1
    return dtw(dist(feat1,feat2))
```

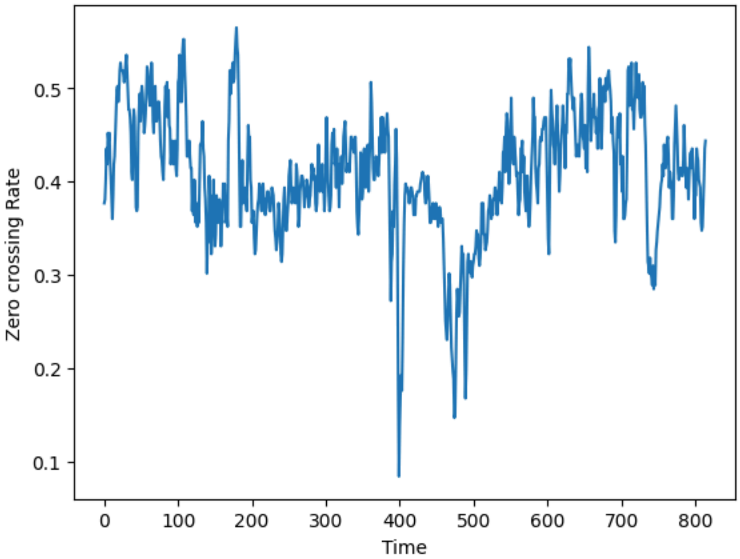
Training

```
import scipy.signal as signal
import numpy
import os

modelob = open("/content/drive/MyDrive/model.txt",'w')

for line in os.listdir("/content/drive/MyDrive/train"):
  if line.endswith(".wav"):
      #Get training file name
      label=line[0]
      filename="/content/drive/MyDrive/train/"+line
      #print(filename)
      #file reading
      wavearr=wavread(filename)
      #Signal pre-emphasis
      wavearr_pre=pre_emphasis(wavearr,0.98)
      #Select window function
      winfunc = signal.hamming(240)
      #Signal framing
      n=enframe(wavearr_pre,240,80,winfunc)
      #vad
      na=vioceextrac(n)
      #Extract features
      feat=mfcc(na,512)
      #Save features and criteria to the output model file
      print('Output results of',filename,' \n')
      print(label, file = modelob)
      print(feat, file = modelob)
      print("_______________________________________________")
      #print(numpy.shape(feat))
```

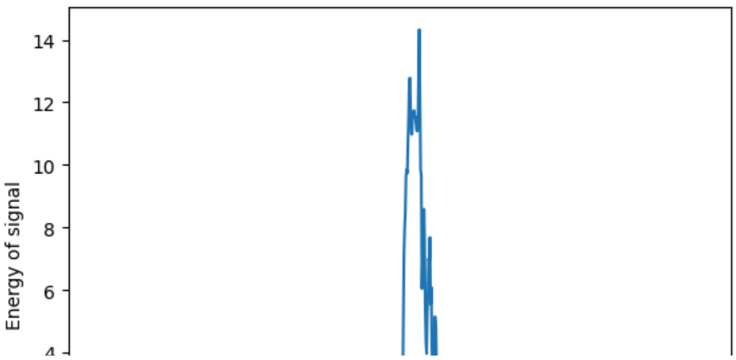
```
        #print(numpy.shape(feat))
print('\n Training complete \n')
modelob.close()
```

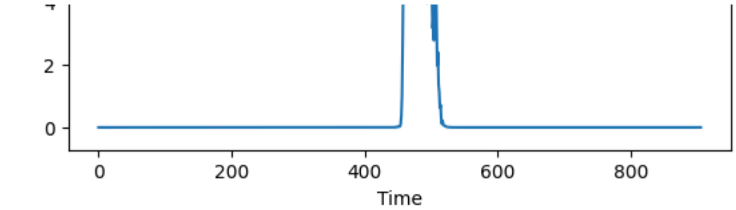
```
Reading WAV file   /content/drive/MyDrive/train/1a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice

<ipython-input-2-38ef7c5dd080>:25: DeprecationWarning: The binary mode of fromstring is deprecated, as it behaves surprisingly or
  wave_data = np.fromstring(str_data, dtype=np.short)
<ipython-input-11-ffa5ce279020>:18: DeprecationWarning: Importing hamming from 'scipy.signal' is deprecated and will raise an err
  winfunc = signal.hamming(240)
```

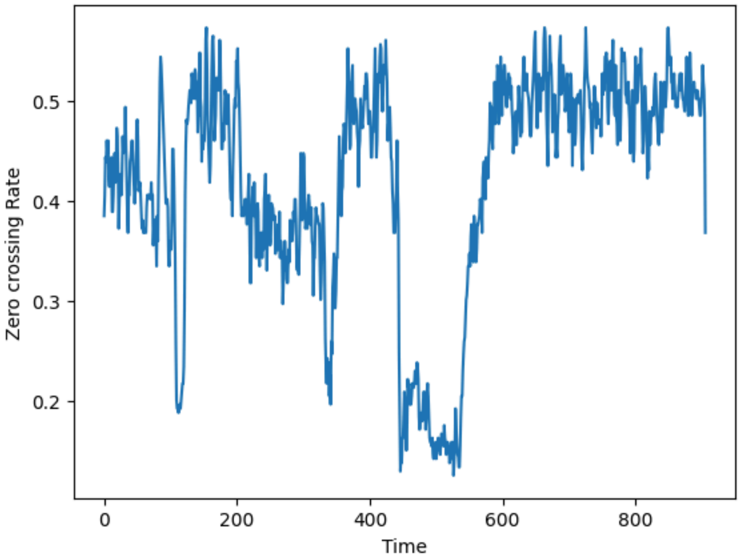




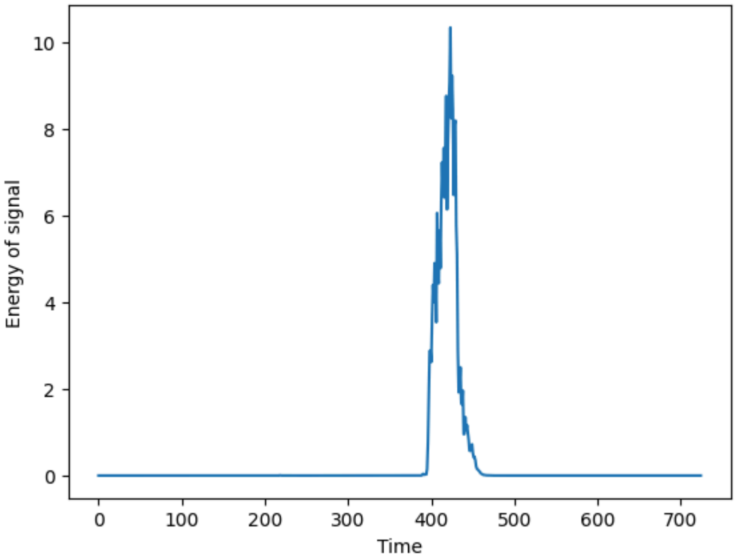

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/1a.wav

___________________________________________________
Reading WAV file   /content/drive/MyDrive/train/2a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

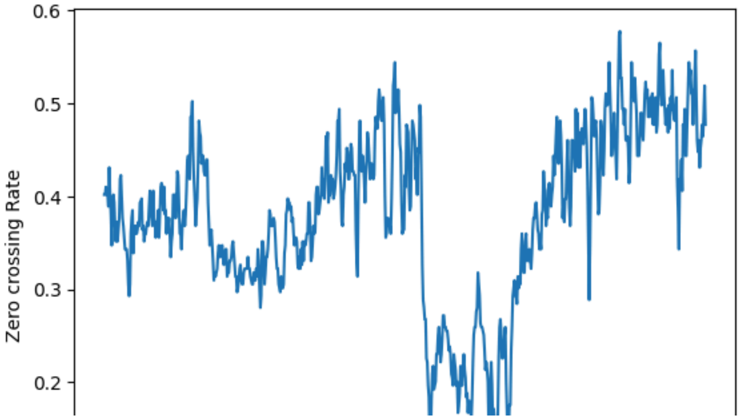


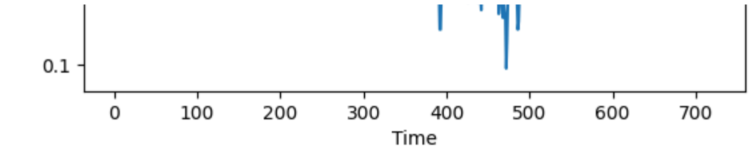




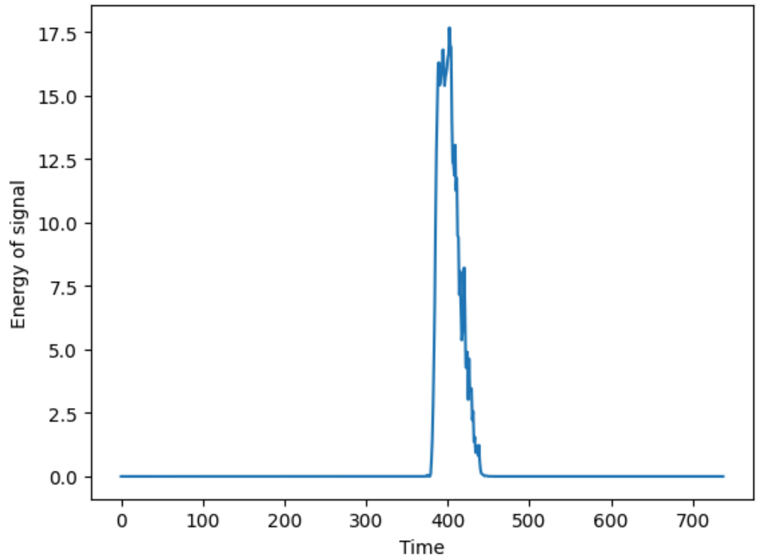

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/2a.wav

___________________________________________________
Reading WAV file   /content/drive/MyDrive/train/0c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

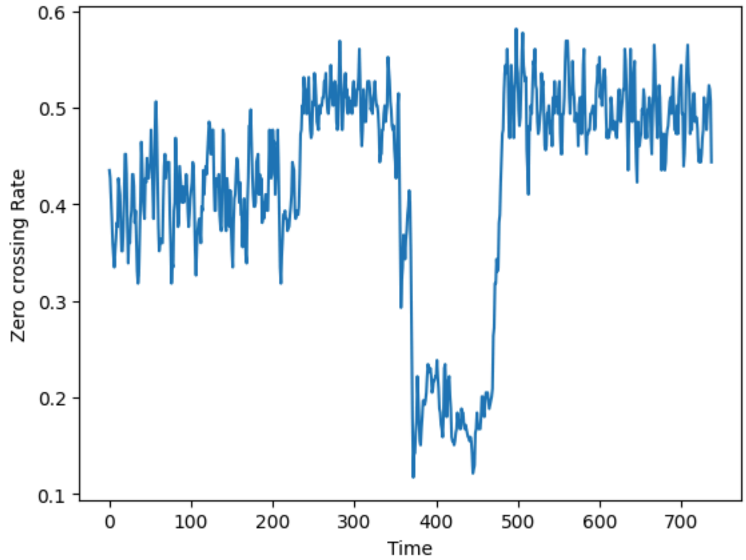




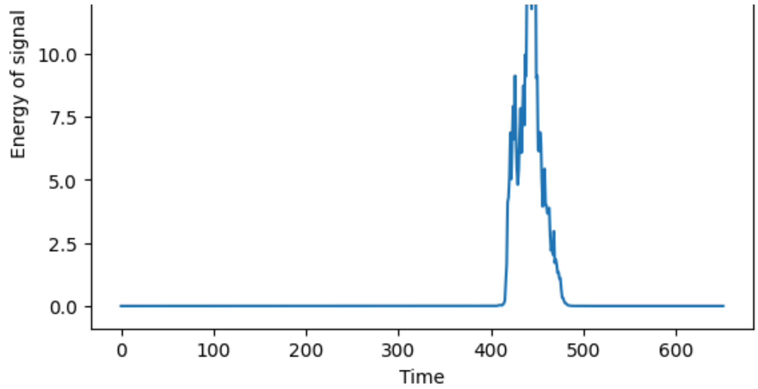


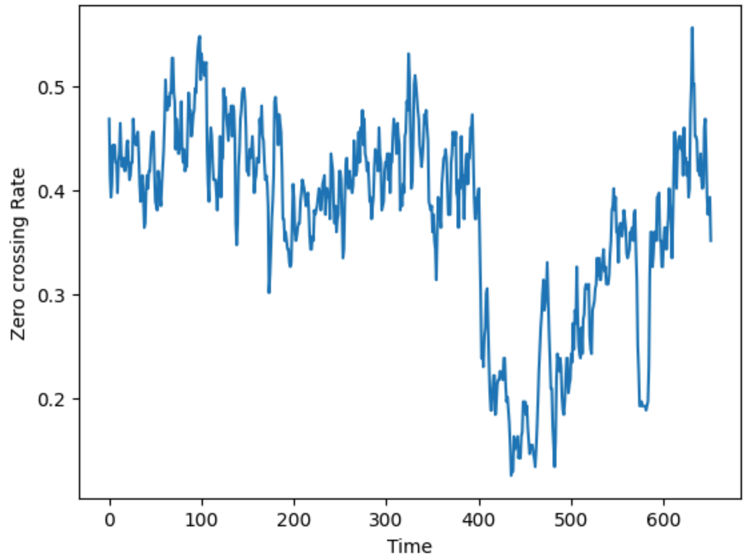

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/0c.wav

Reading WAV file   /content/drive/MyDrive/train/2b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```



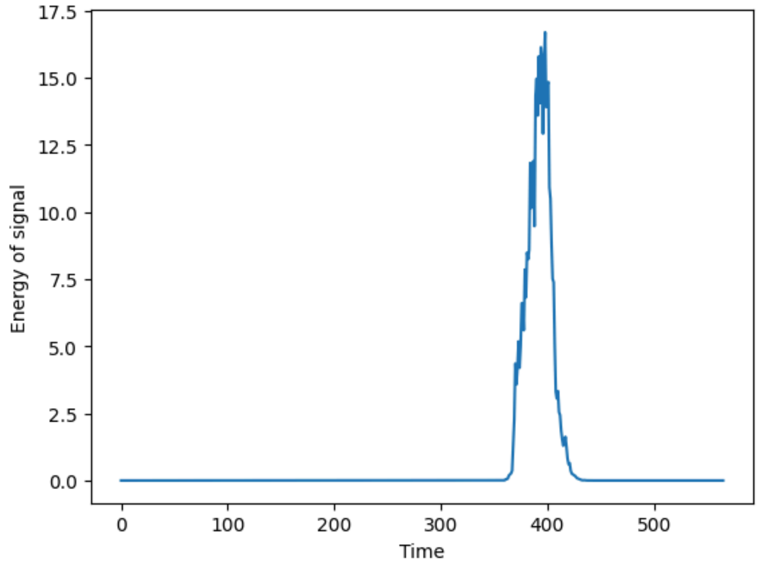


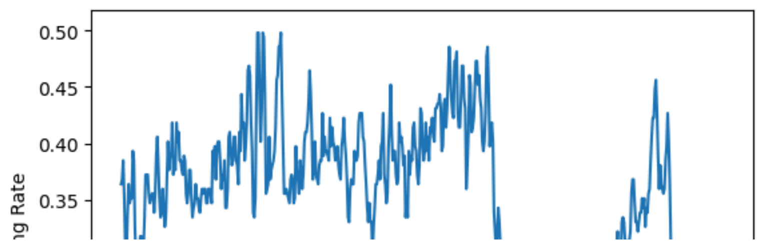

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/2b.wav

Reading WAV file   /content/drive/MyDrive/train/0b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

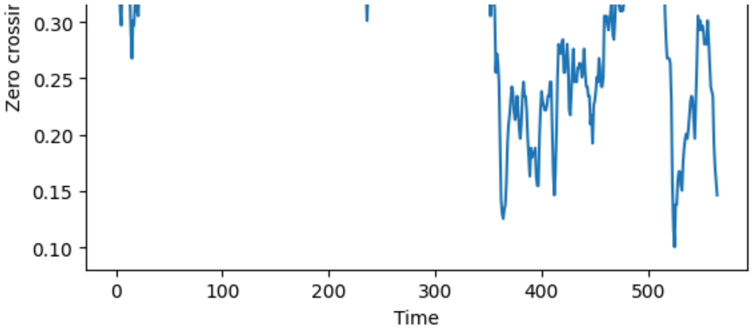




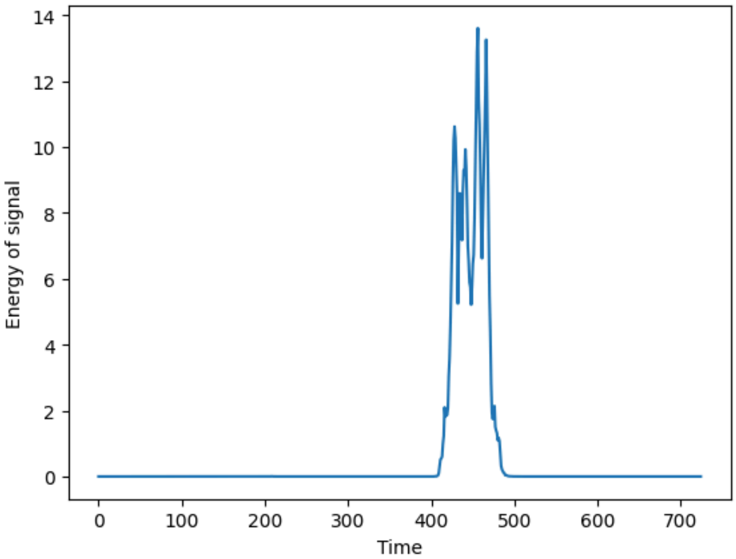

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/0b.wav

________________________________________________
Reading WAV file   /content/drive/MyDrive/train/0a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

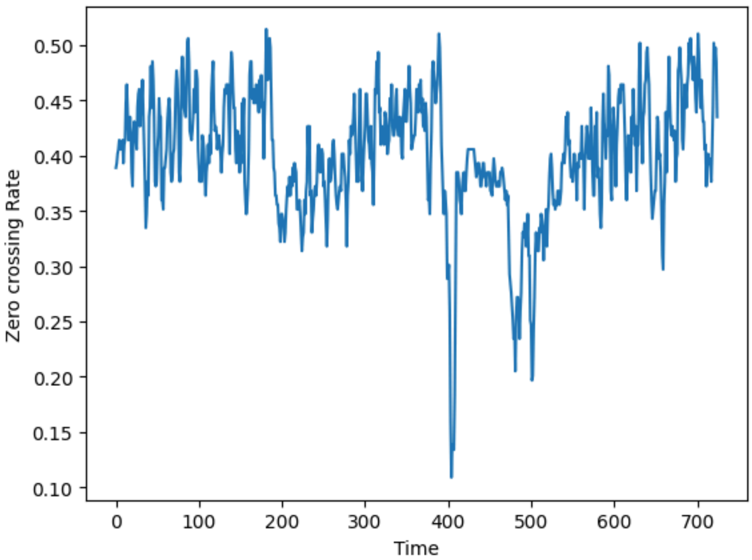




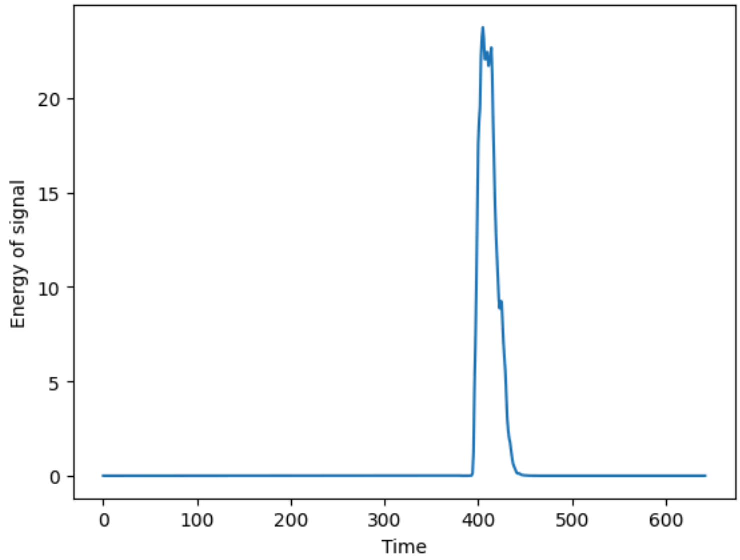


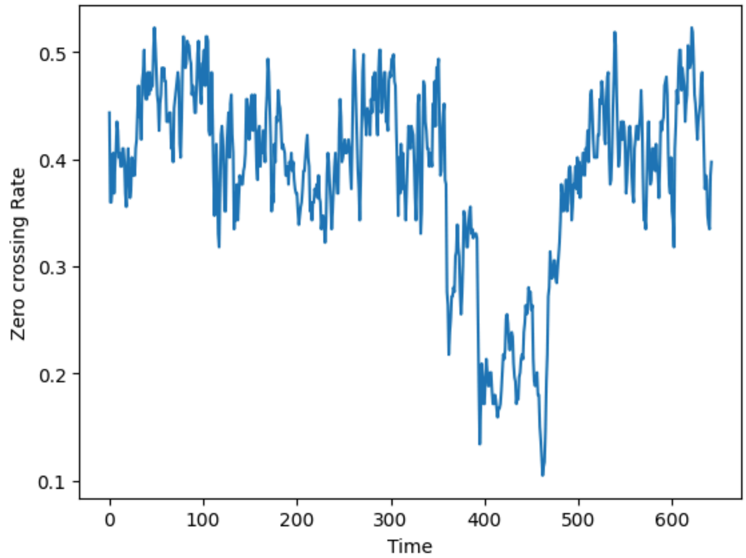

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/0a.wav

___________________________________________________
Reading WAV file   /content/drive/MyDrive/train/1b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```



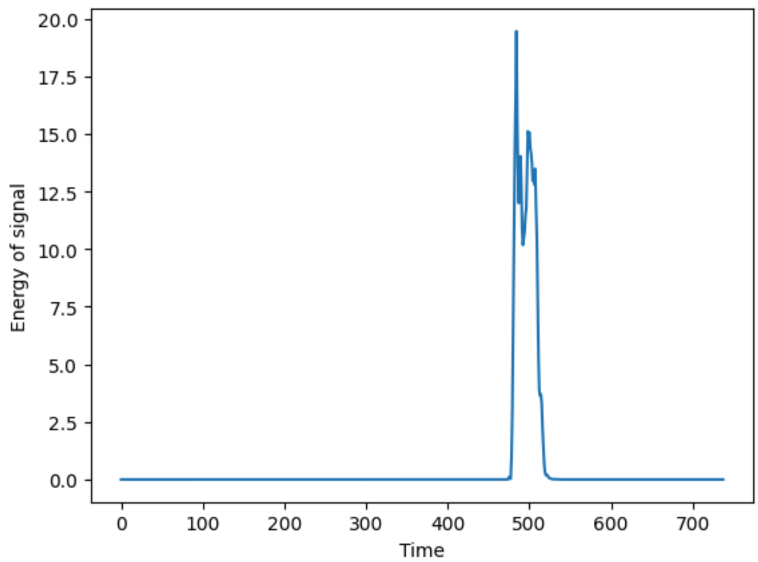


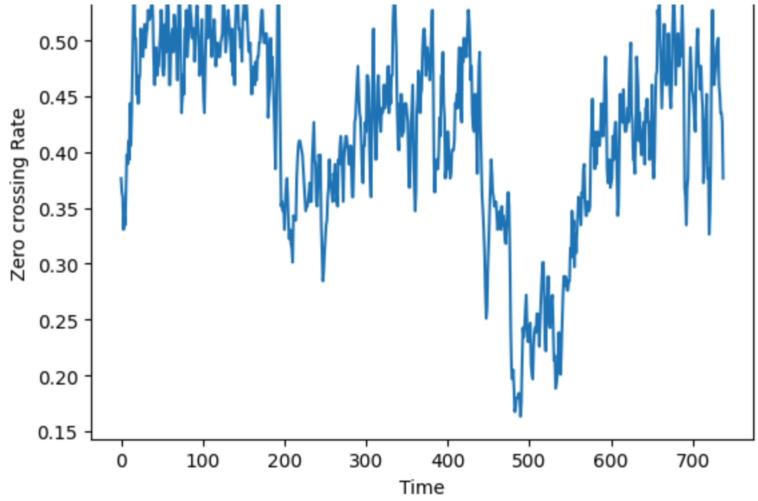

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/1b.wav

___________________________________________________
Reading WAV file   /content/drive/MyDrive/train/3b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```



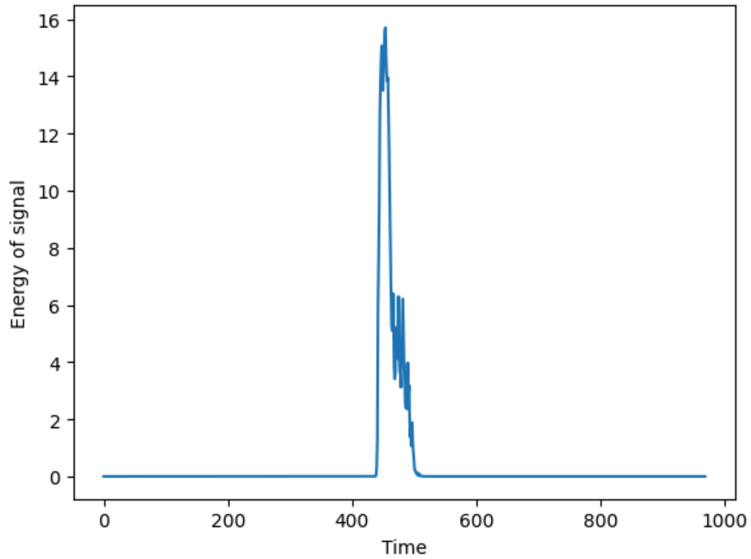


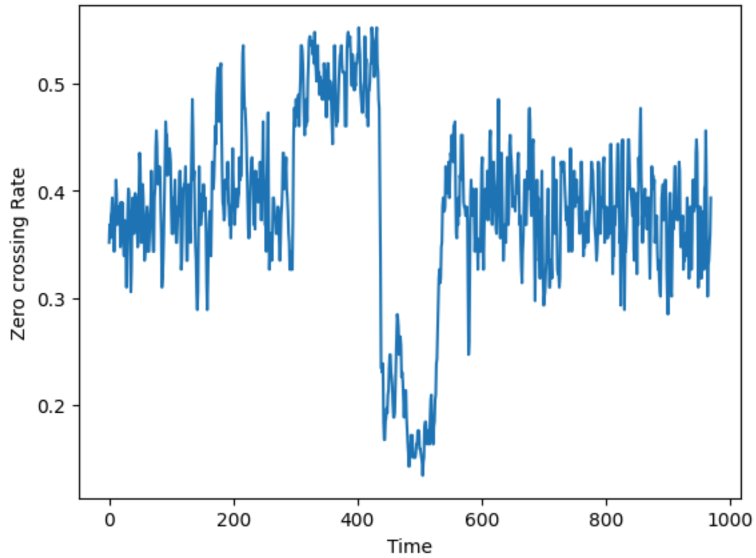

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/3b.wav

___________________________________________________________________
Reading WAV file   /content/drive/MyDrive/train/3a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```





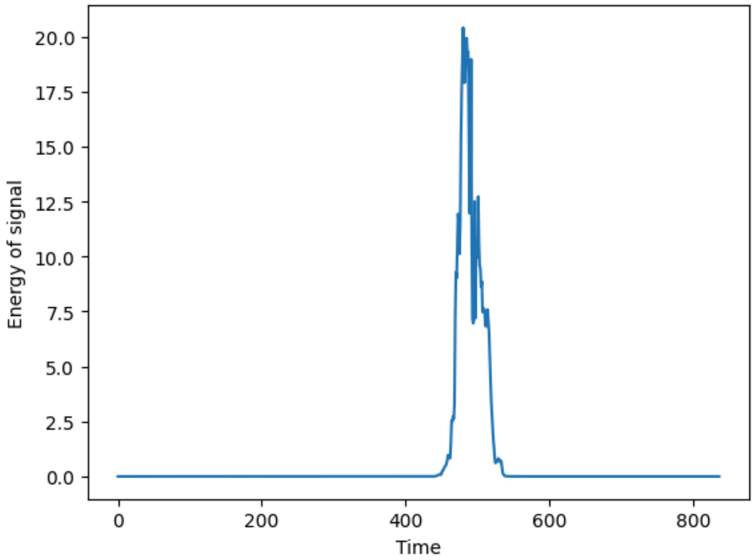

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/3a.wav

__________________________________________________
Reading WAV file   /content/drive/MyDrive/train/2c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

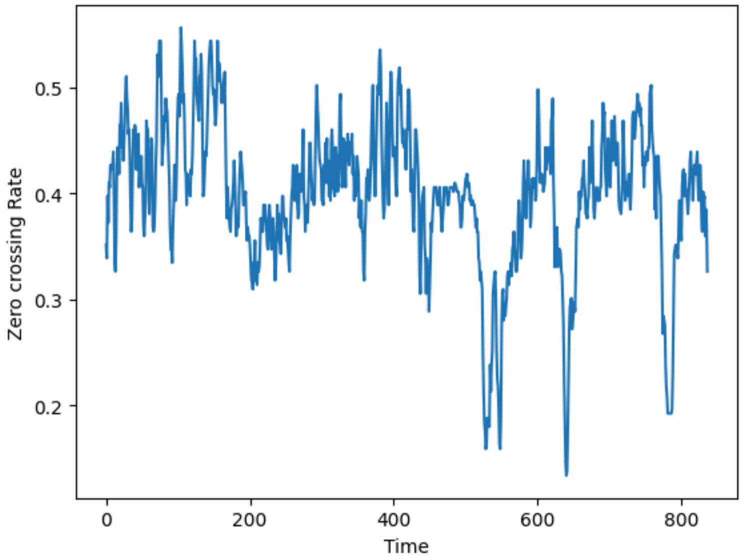




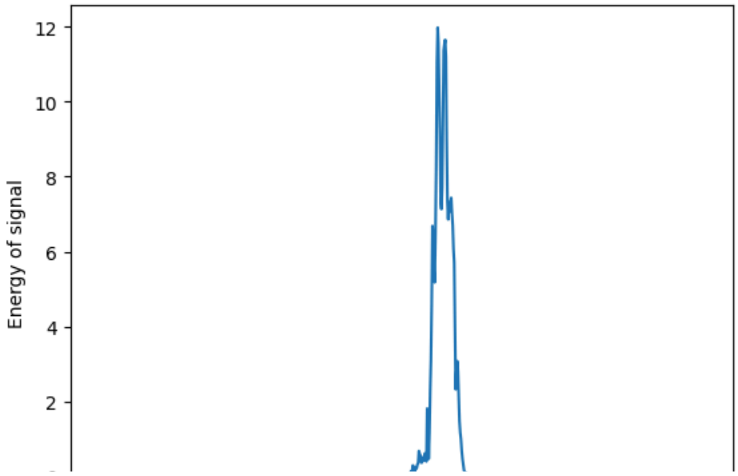

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/2c.wav

__________________________________________________
Reading WAV file   /content/drive/MyDrive/train/1c.wav ---
```

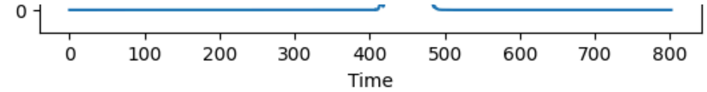
```
Pre emphasis

Signal framing and windowing

Extracting active voice
```

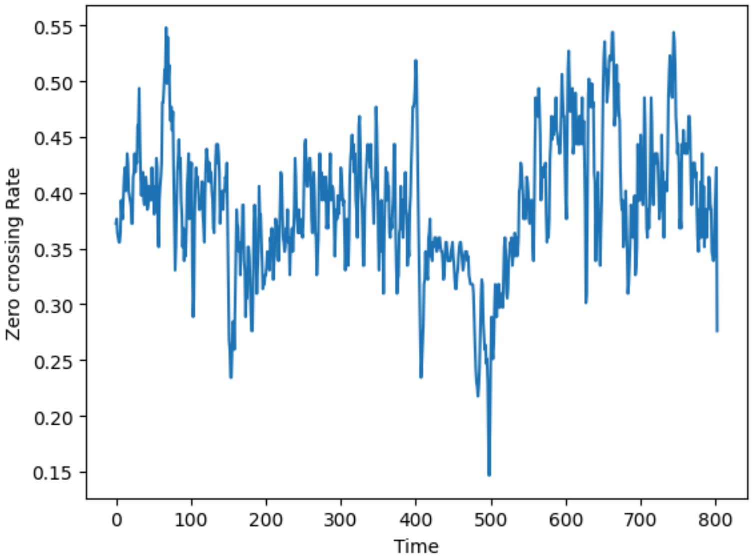




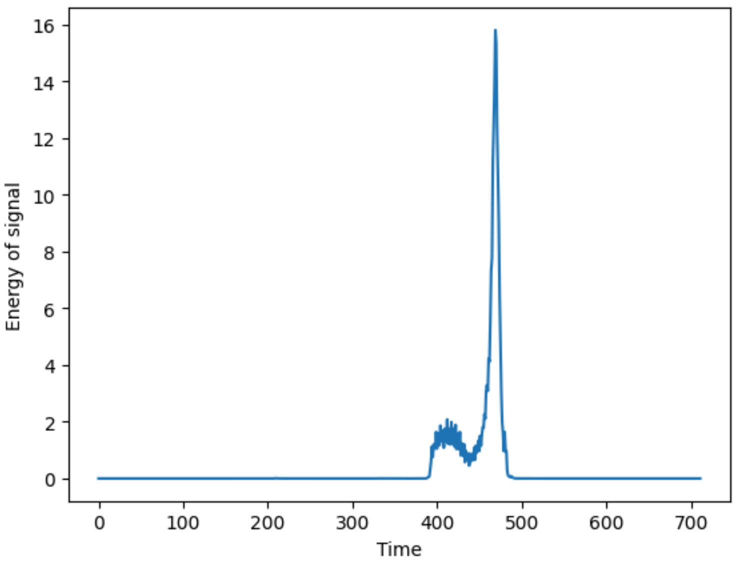

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/1c.wav

________________________________________________
Reading WAV file   /content/drive/MyDrive/train/7b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

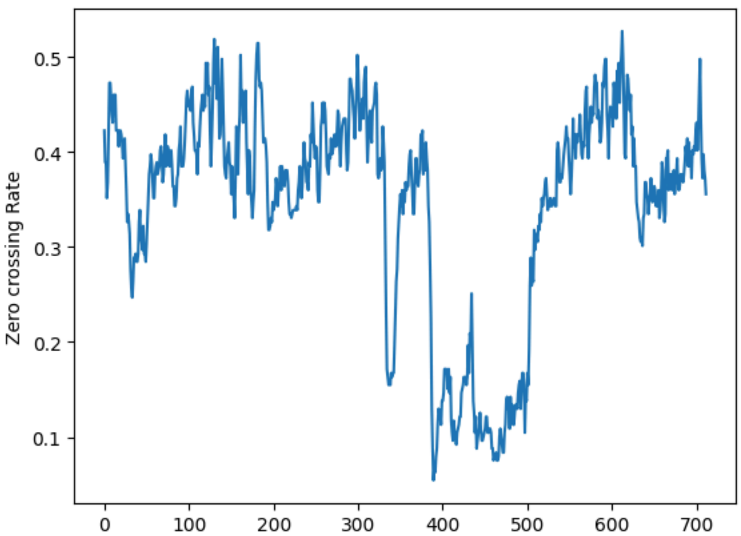






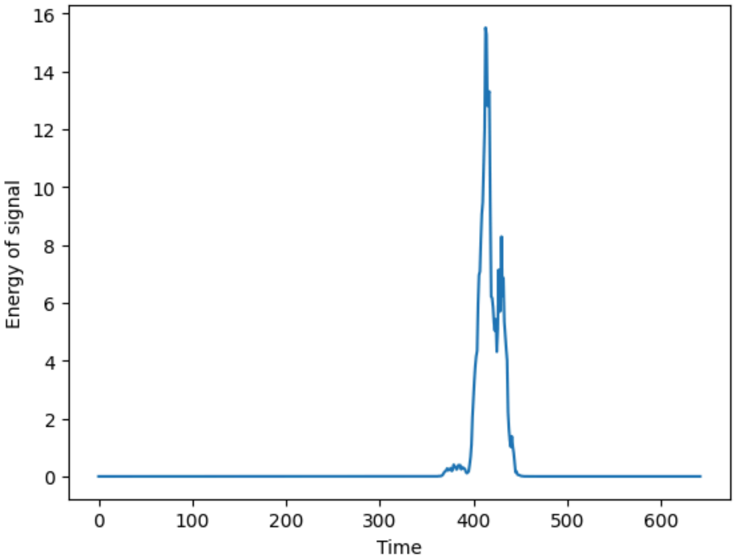

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/7b.wav

_______________________________________________
Reading WAV file   /content/drive/MyDrive/train/5c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

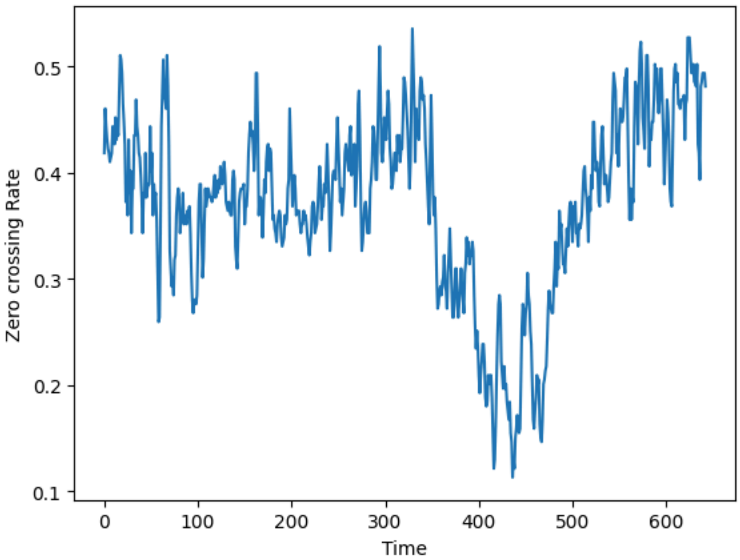




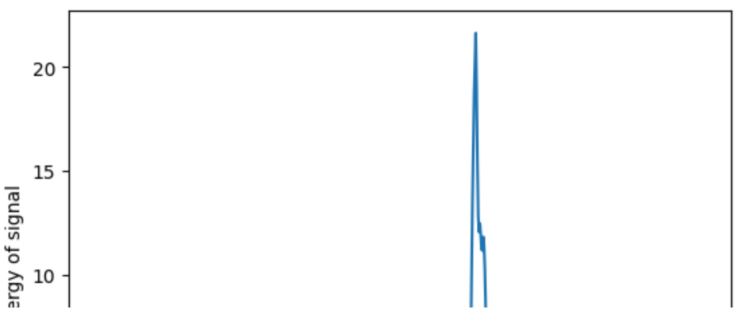
Time

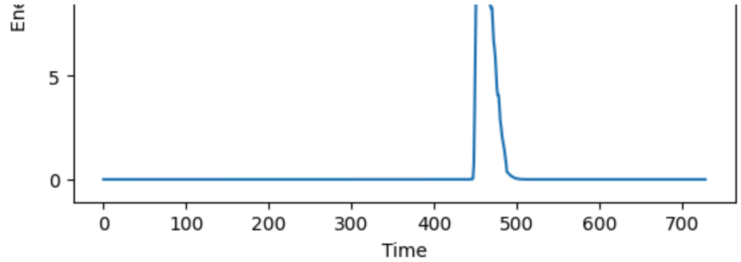
```
Computing MFCC features

Output results of /content/drive/MyDrive/train/5c.wav

________________________________________________
Reading WAV file   /content/drive/MyDrive/train/4c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

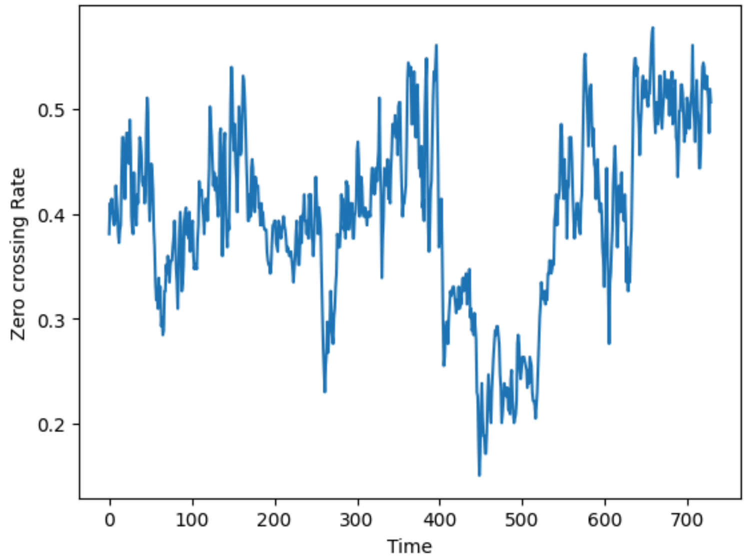




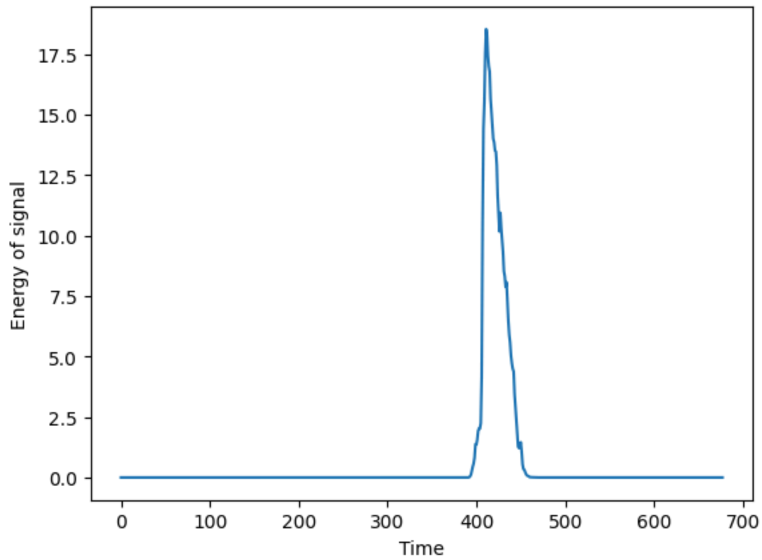

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/4c.wav

________________________________________________
Reading WAV file   /content/drive/MyDrive/train/3c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

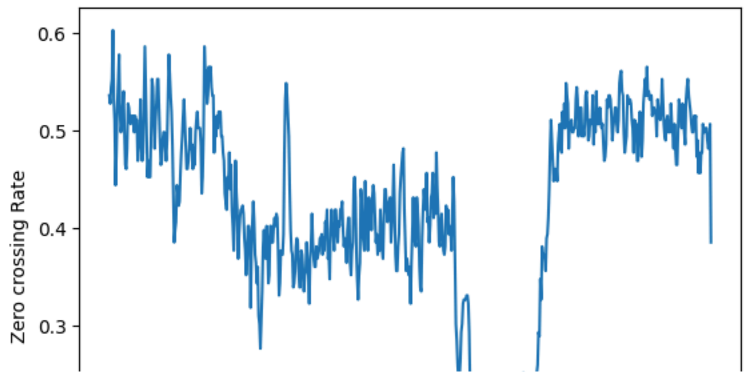


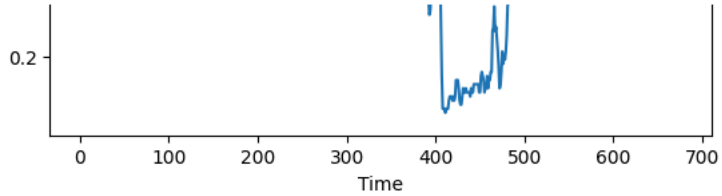





```
Computing MFCC features

Output results of /content/drive/MyDrive/train/3c.wav

_________________________________________________
Reading WAV file   /content/drive/MyDrive/train/8c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```







Computing MFCC features

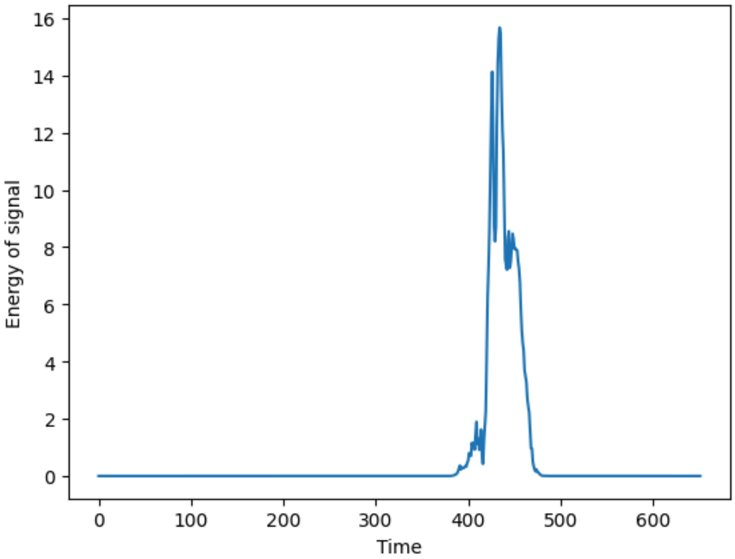
Output results of /content/drive/MyDrive/train/8c.wav

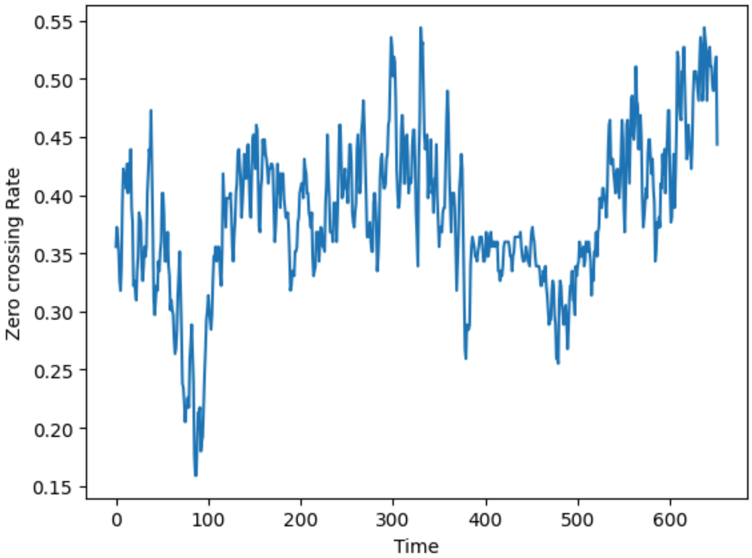
Reading WAV file   /content/drive/MyDrive/train/7a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice





Computing MFCC features

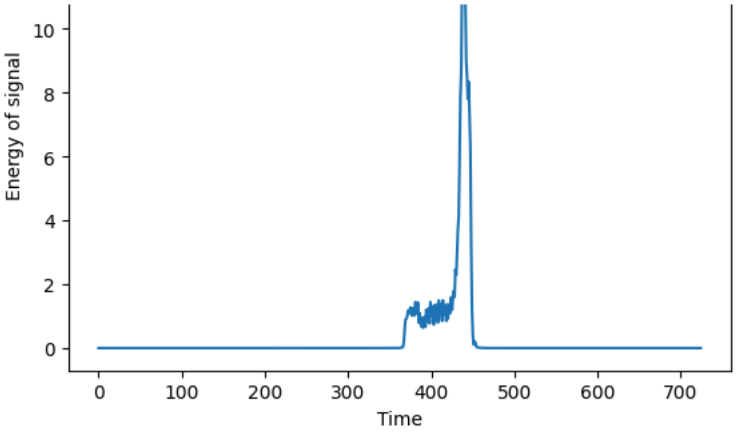
Output results of /content/drive/MyDrive/train/7a.wav

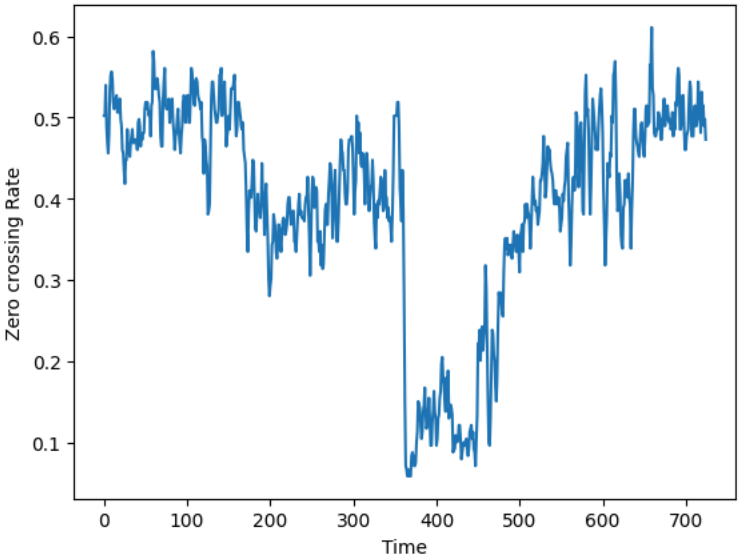
Reading WAV file   /content/drive/MyDrive/train/5a.wav ---

Pre emphasis

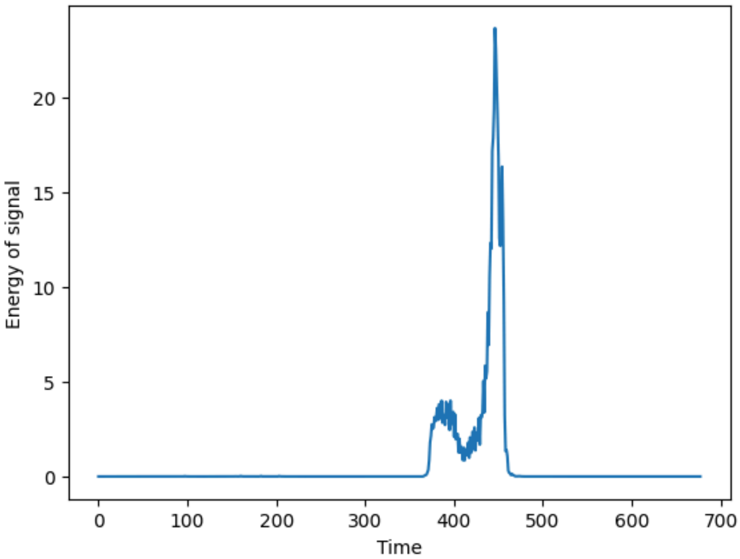
Signal framing and windowing

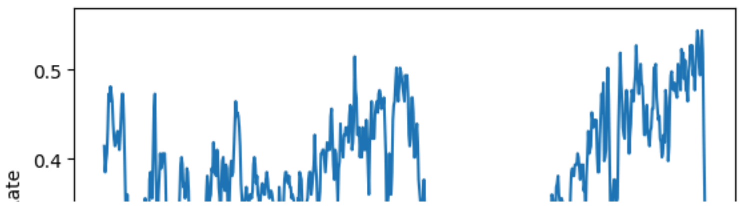
Extracting active voice

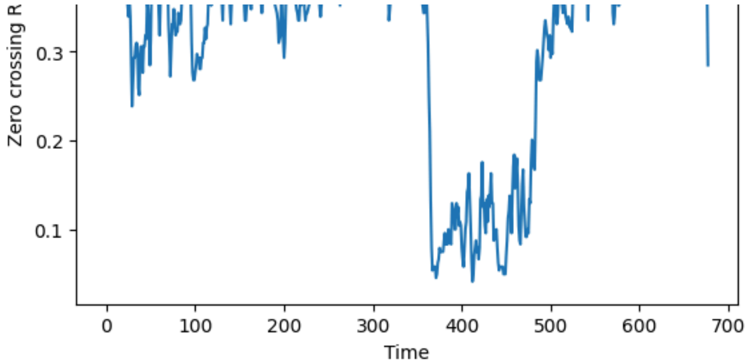




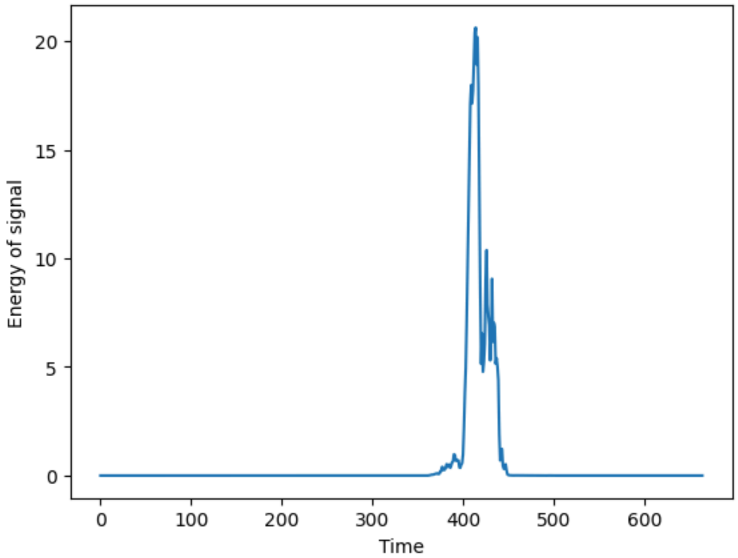

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/5a.wav

________________________________________________
Reading WAV file   /content/drive/MyDrive/train/5b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

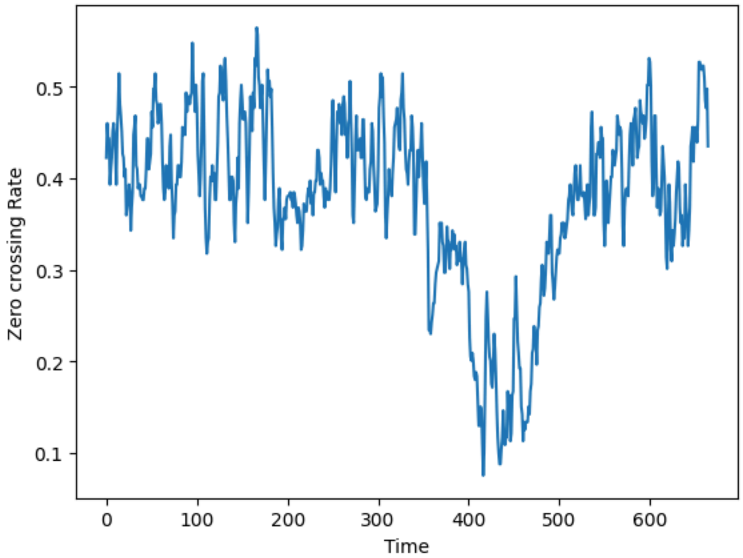




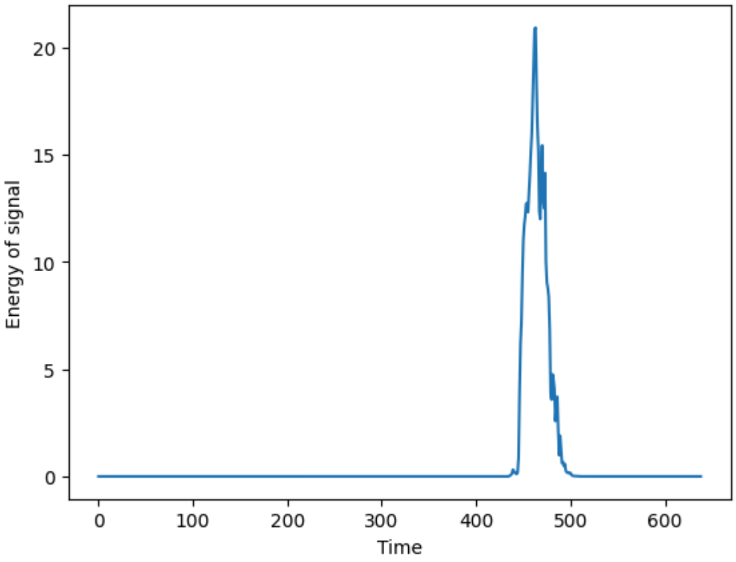


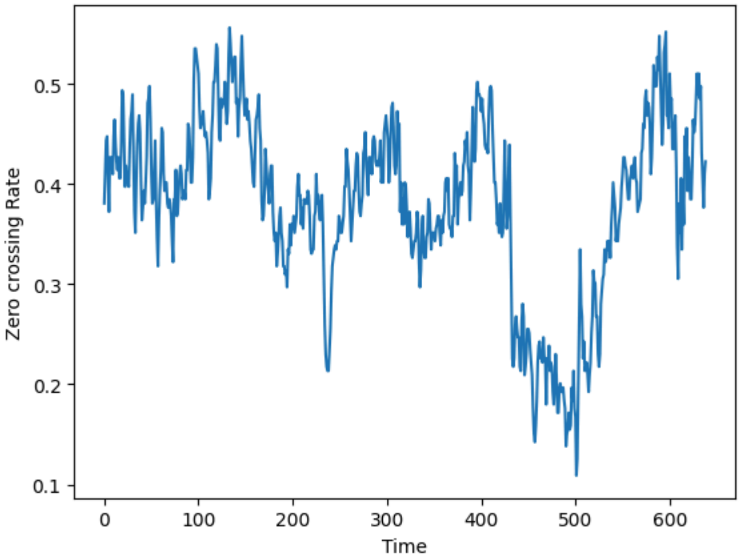

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/5b.wav

_______________________________________________
Reading WAV file   /content/drive/MyDrive/train/4a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```



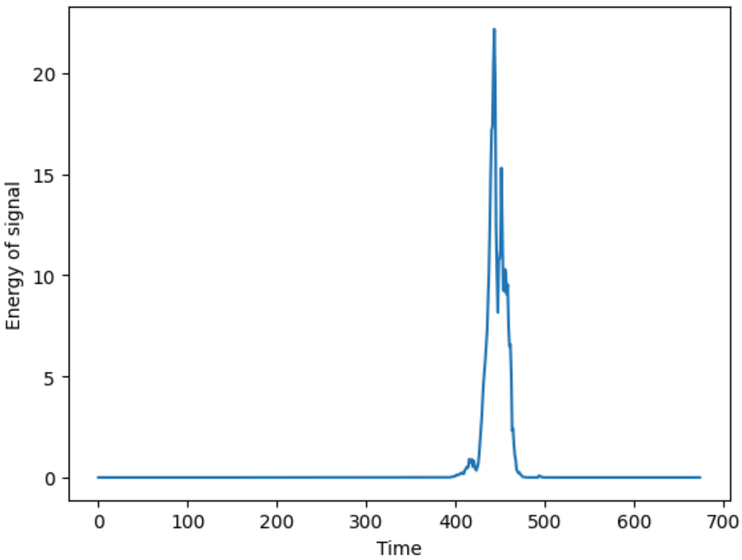


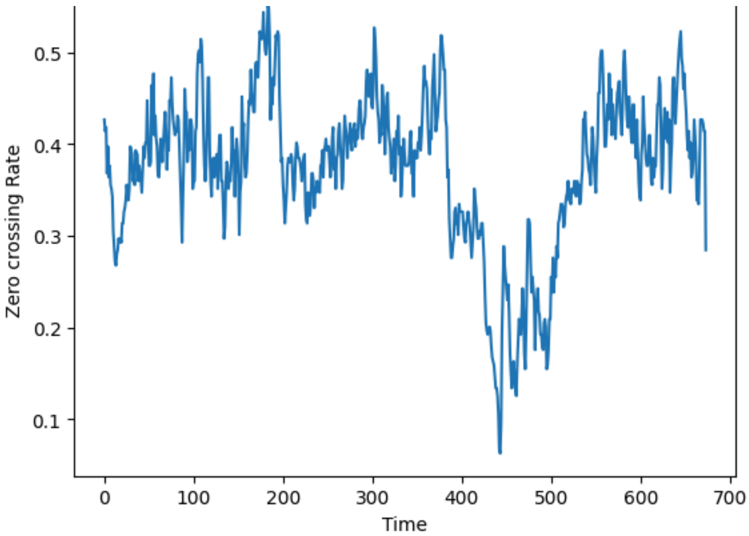

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/4a.wav

_______________________________________________
Reading WAV file   /content/drive/MyDrive/train/6a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```



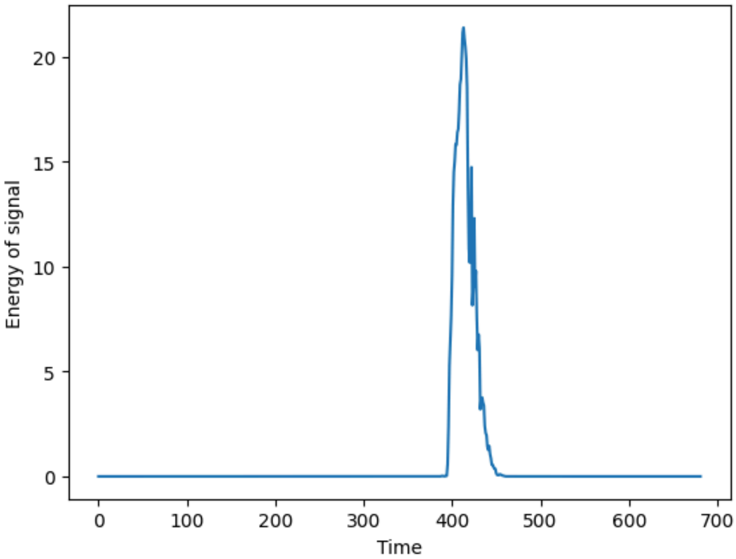


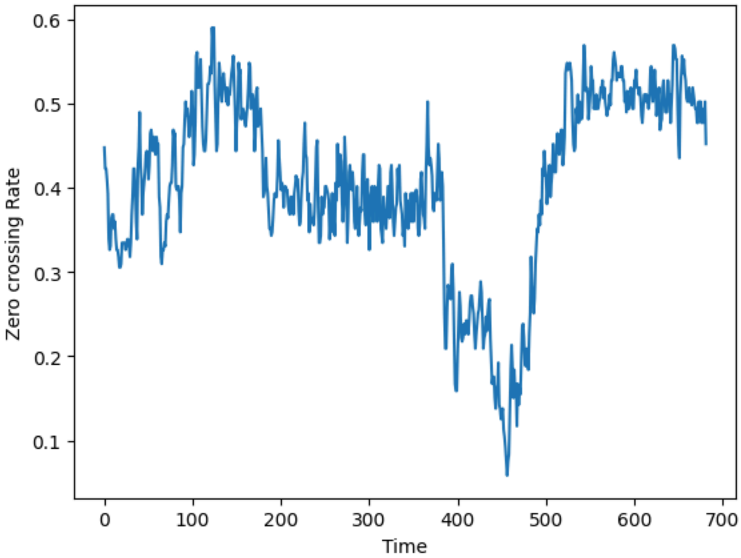

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/6a.wav

_________________________________________________
Reading WAV file   /content/drive/MyDrive/train/4b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```





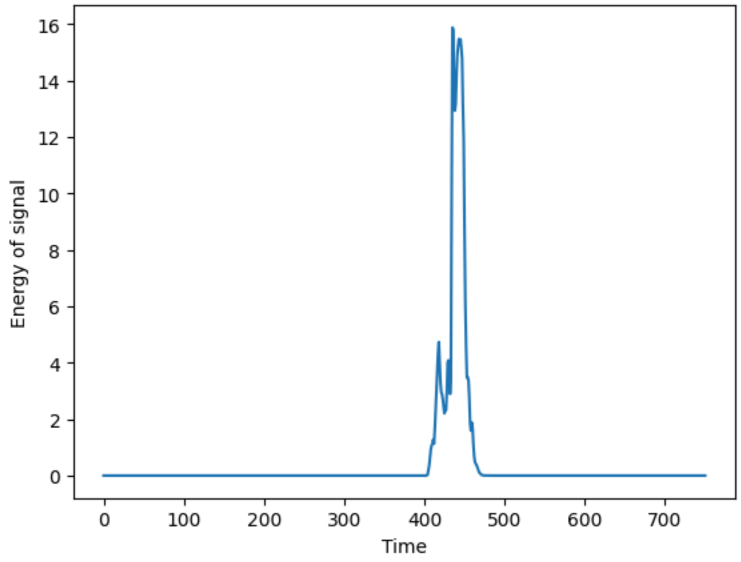

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/4b.wav

_________________________________________________
Reading WAV file   /content/drive/MyDrive/train/6c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

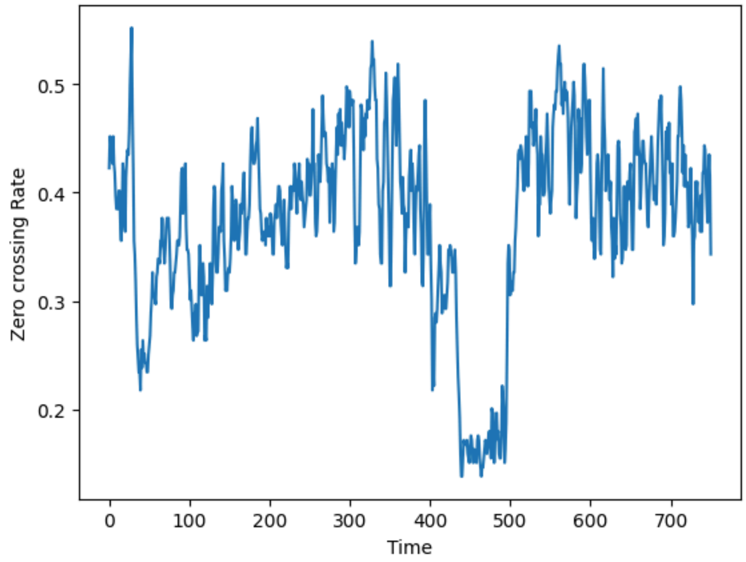





```
Computing MFCC features

Output results of /content/drive/MyDrive/train/6c.wav
```

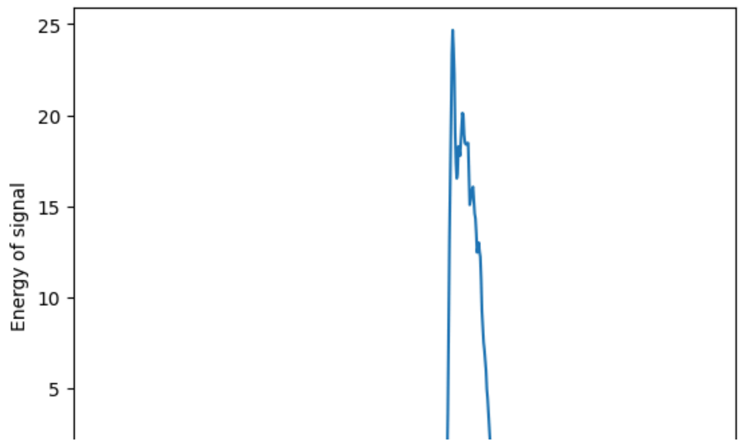
```
Reading WAV file   /content/drive/MyDrive/train/8b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

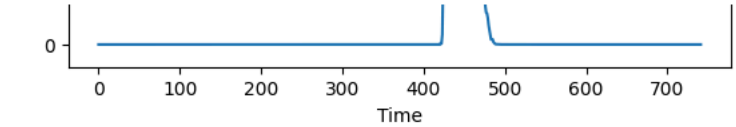


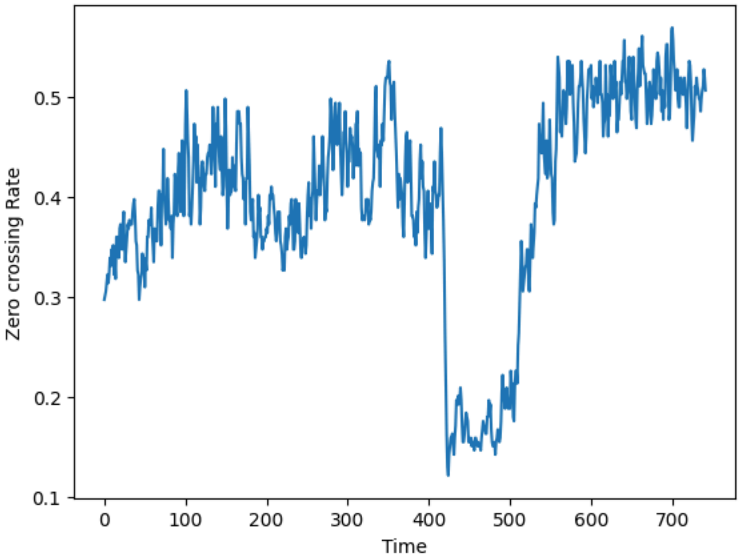



```
Computing MFCC features

Output results of /content/drive/MyDrive/train/8b.wav
```

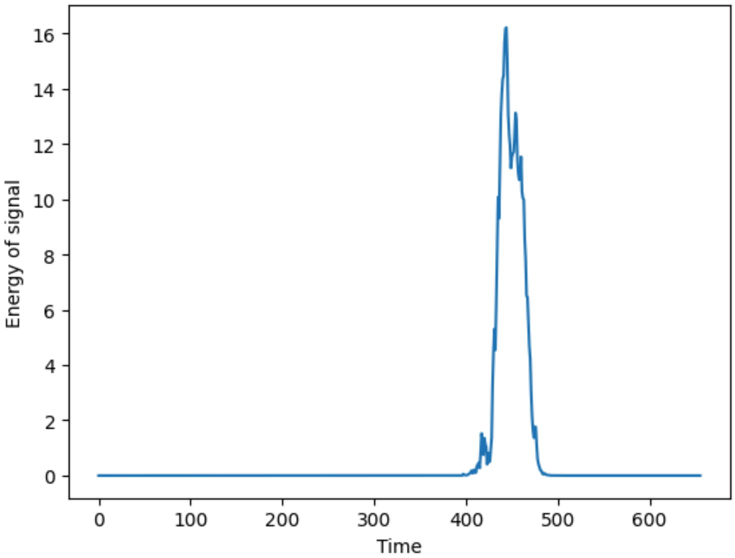
```
Reading WAV file   /content/drive/MyDrive/train/8a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

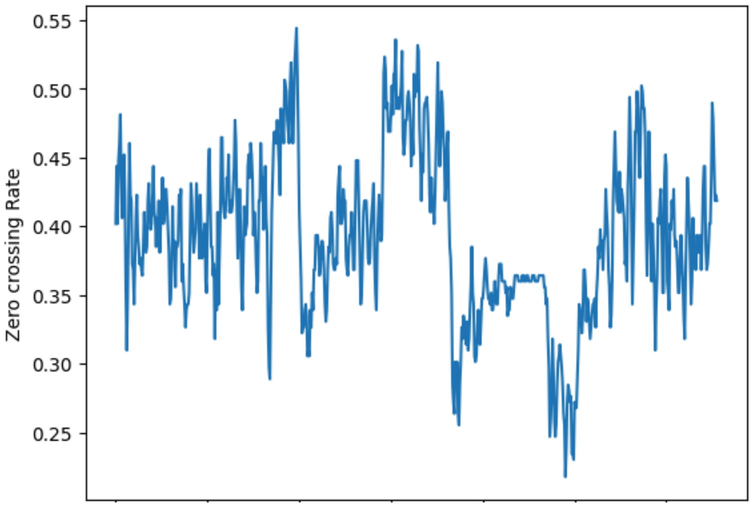




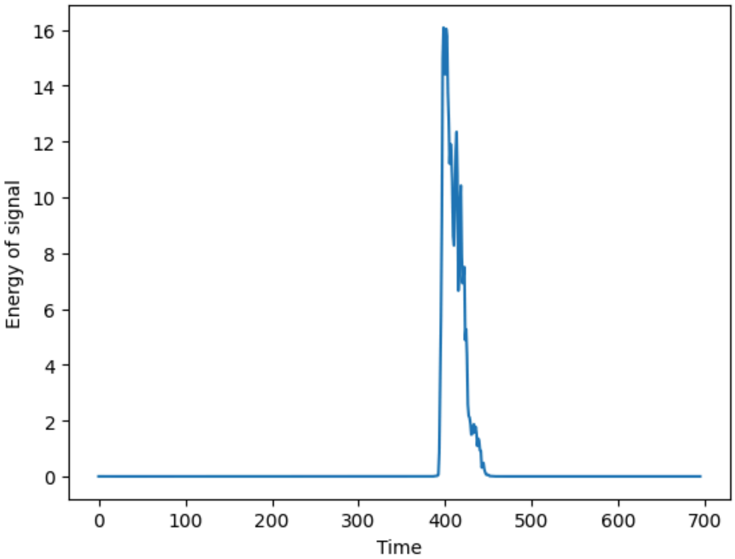


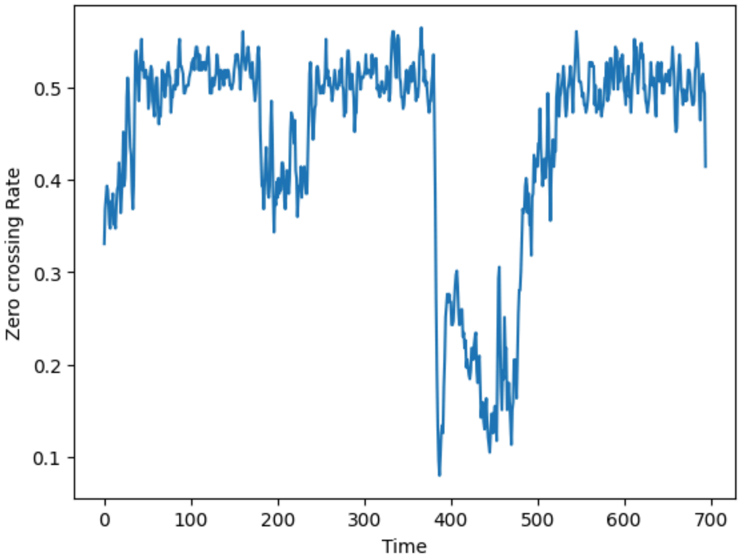

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/8a.wav

_____________________________________________
Reading WAV file   /content/drive/MyDrive/train/7c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```



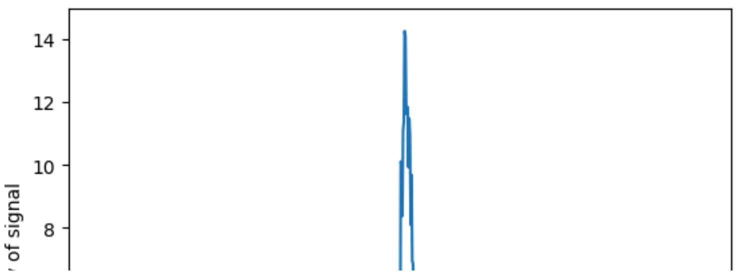


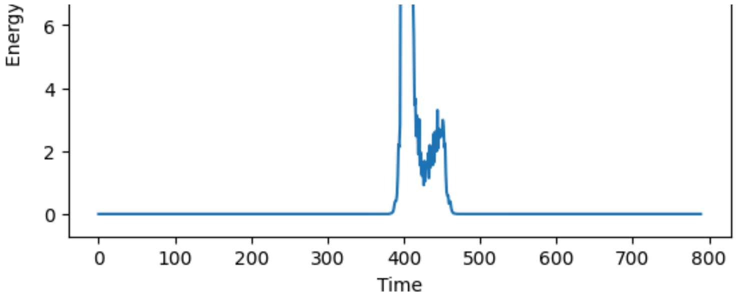

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/7c.wav

______________________________________________
Reading WAV file   /content/drive/MyDrive/train/6b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

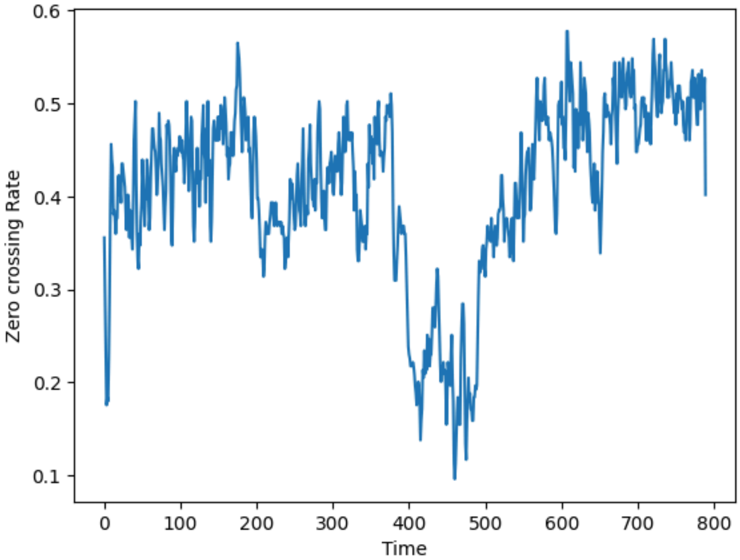




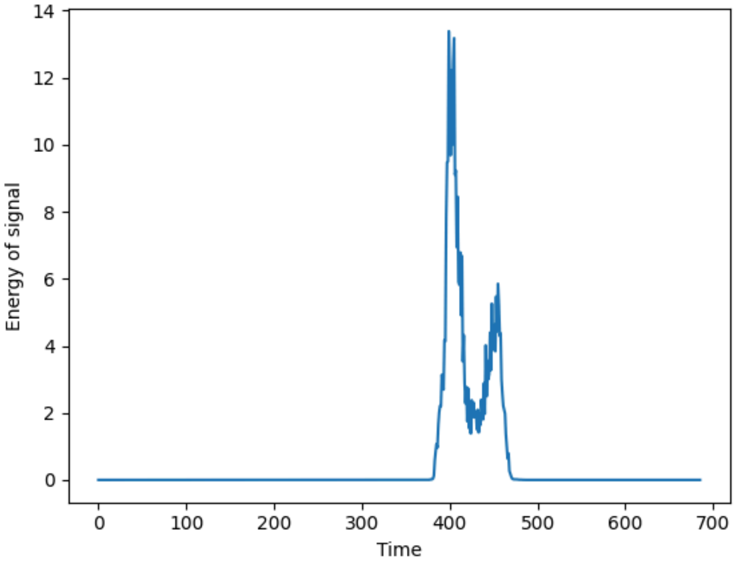

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/6b.wav

______________________________________________
Reading WAV file   /content/drive/MyDrive/train/9a.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

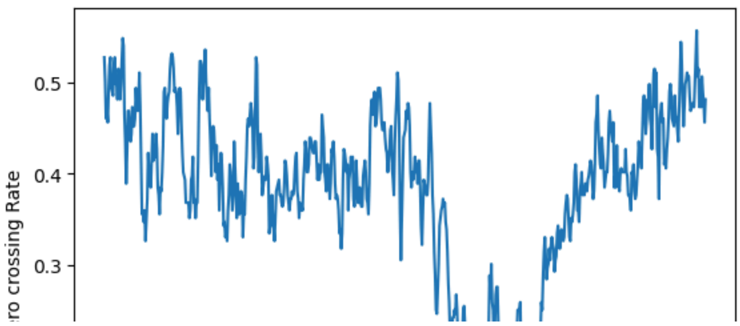


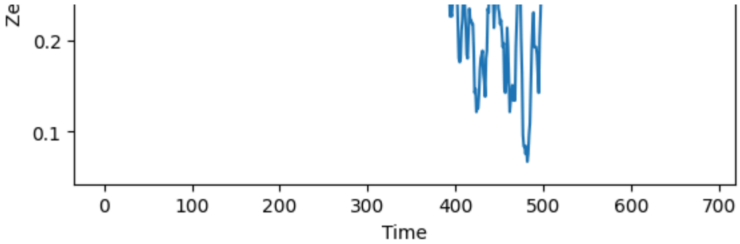




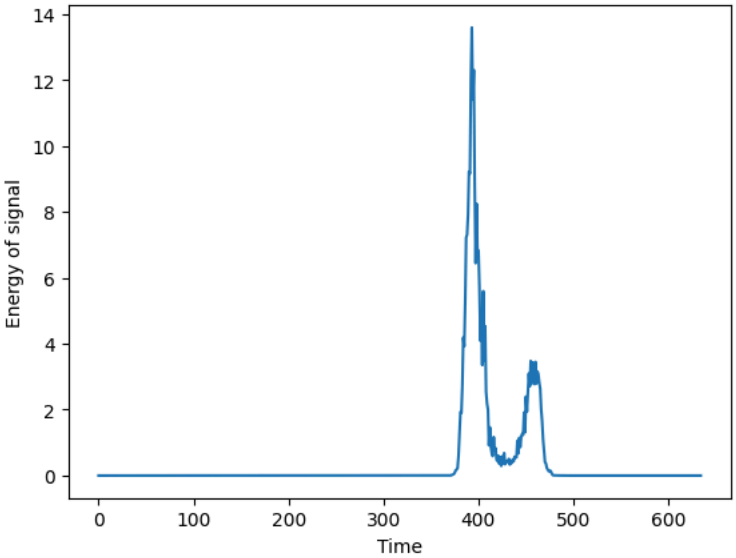

```
Computing MFCC features

Output results of /content/drive/MyDrive/train/9a.wav

_________________________________________________
Reading WAV file   /content/drive/MyDrive/train/9b.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

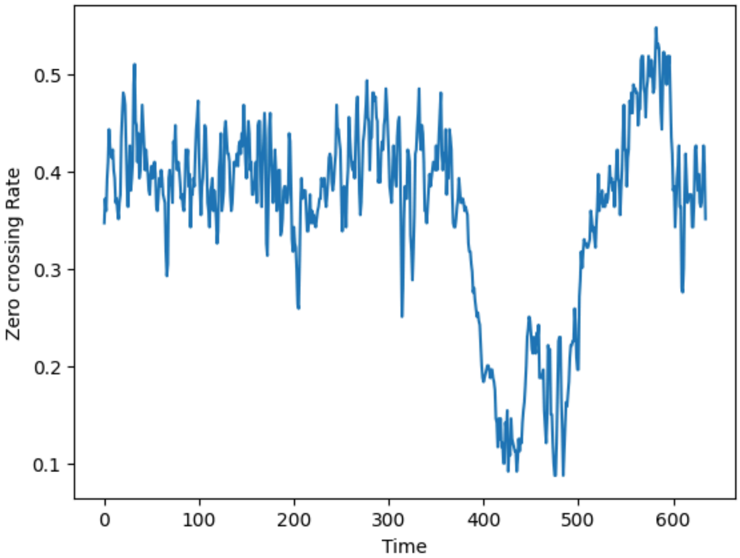







```
Computing MFCC features

Output results of /content/drive/MyDrive/train/9b.wav

____________________________________________________
Reading WAV file   /content/drive/MyDrive/train/9c.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```






```
Computing MFCC features

Output results of /content/drive/MyDrive/train/9c.wav

____________________________________________________

 Training complete
```

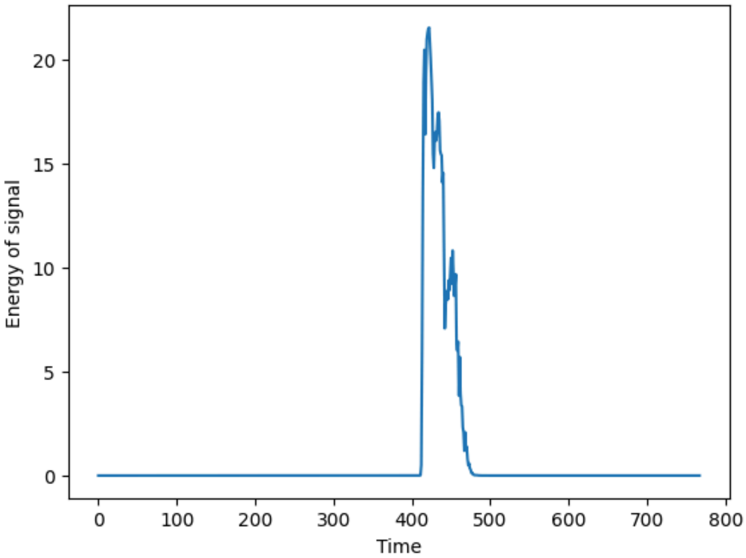
Testing

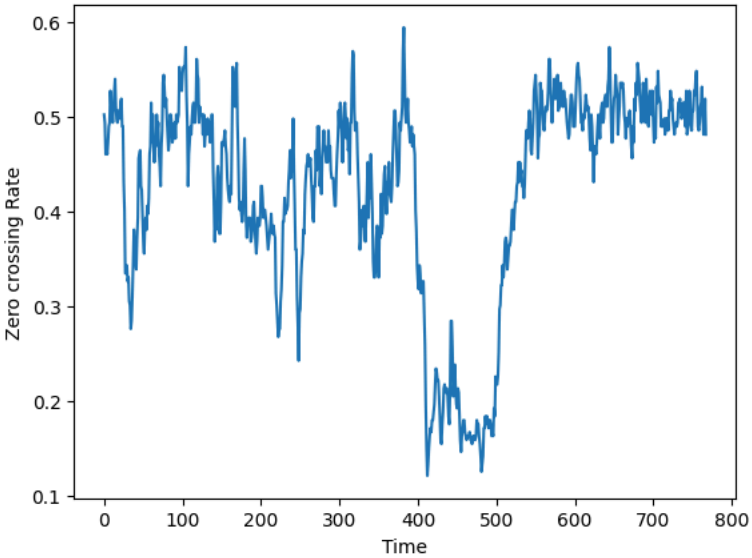
```
import re
import scipy.signal as signal
import numpy
```

```
import numpy
import os

total = 0
acc = 0
for line in os.listdir("/content/drive/MyDrive/test"):
  if line.endswith(".wav"):
    total += 1
    label=line[0]
    print("Actual Label : ", label)
    filename="/content/drive/MyDrive/test/"+line
    #file reading
    wavearr=wavread(filename)
    #Signal pre-emphasis
    wavearr_pre=pre_emphasis(wavearr,0.98)
    #Select window function
    winfunc = signal.hamming(240)
    #Signal framing
    n=enframe(wavearr_pre,240,80,winfunc)
    #vad
    na=vioceextrac(n)
    #Extract features
    feattest=mfcc(na,512)
    #print(numpy.shape(feattest))

    modelob=open("/content/drive/MyDrive/model1.txt")
    print(' DTW \n')
    i=0

    dist1=[]
    label=[]
    mframes=modelob.readlines()
    #print(len(frames))
    for line1 in mframes:
      i+=1
      mline=line1.strip()
      if i==1 and len(mline)==1:
          label.append(mline)

          featarr=[]
          nf=0                                                                                # No. of FVs extracted from each model
      if i>1 and len(mline)==1:
          #Regenerate numpy matrix and unify specifications
          feat=numpy.array(featarr,dtype=numpy.float64)
          feattrain=feat.reshape(nf,m)
          #print(feattrain)
          featarr=[]
          #Calculate the dtw distance from the test signal to each signal in the model
          dist1.append(score(feattrain,feattest))
          #print(nf,m)
          nf=0
          label.append(mline)

      if i!=len(mframes) and len(mline)>1:
          #print(mline)
          mline=mline.strip('[]')
          mline=mline.strip()
          #print(mline)
          mlinearr=re.split('\s+',mline)
          #print(len(mlinearr))
          #print(mlinearr)
          featarr.append(mlinearr)
          m=len(mlinearr)
          nf+=1
      if i==len(mframes) and len(mline)>1:
          #print(mline)
          mline=mline.strip('[]')
          mline=mline.strip()
          #print(mline)
          mlinearr=re.split('\s+',mline)
          #print(len(mlinearr))
          #print(mlinearr)
          featarr.append(mlinearr)
          m=len(mlinearr)
          nf+=1
          #Regenerate numpy matrix and unify specifications
          feat=numpy.array(featarr,dtype=numpy.float64)
          feattrain=feat.reshape(nf,m)
          #print(feattrain)
          featarr=[]
          #Calculate the dtw distance from the test signal to each signal in the model
          dist1.append(score(feattrain,feattest))
          #print(nf,m)
```

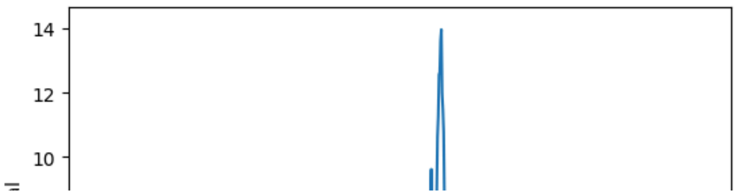
```
    if dist1 != []:
      print('Min distance matching \n')
      #Search for the smallest among all distances
      labelnum=dist1.index(min(dist1))
      print('Output \n')
      #Output the label corresponding to the minimum distance signal as the recognition result.
      print(label[labelnum])
      print("___________________________________________________")
      if line[0] == label[labelnum]:
        acc += 1
print("Test Accuracy :", (acc/total)*100, "%")
modelob.close
print('\n Recognition complete \n')
```

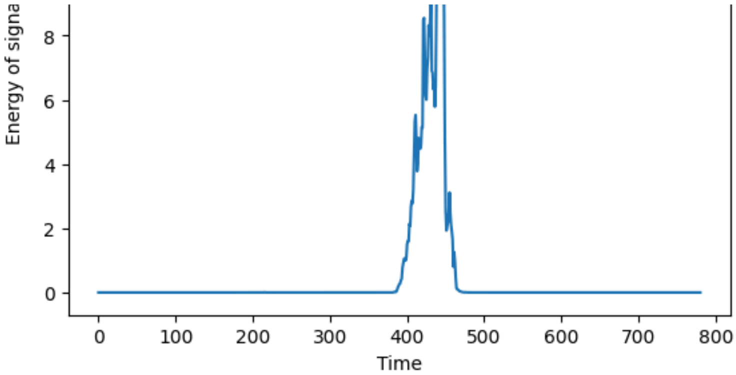
```
Actual Label :  2
Reading WAV file   /content/drive/MyDrive/test/2t.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice

<ipython-input-2-38ef7c5dd080>:25: DeprecationWarning: The binary mode of fromstring is deprecated, as it behaves surprisingly or
  wave_data = np.fromstring(str_data, dtype=np.short)
<ipython-input-12-347b22e80d44>:19: DeprecationWarning: Importing hamming from 'scipy.signal' is deprecated and will raise an err
  winfunc = signal.hamming(240)
```

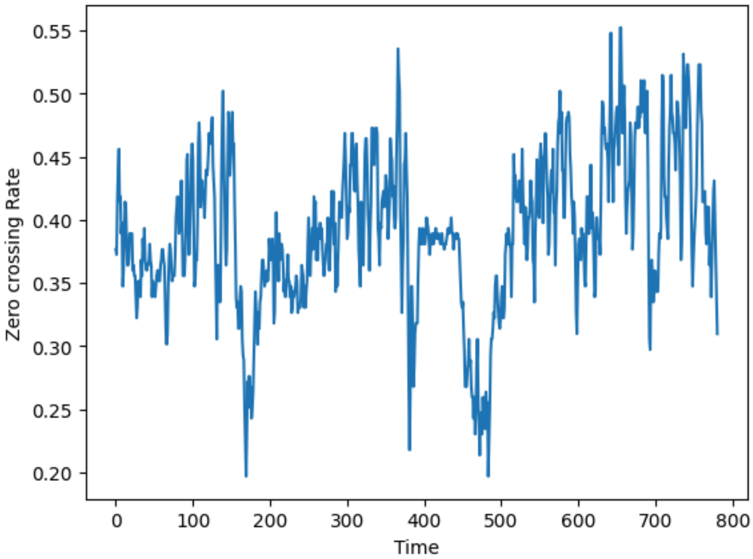




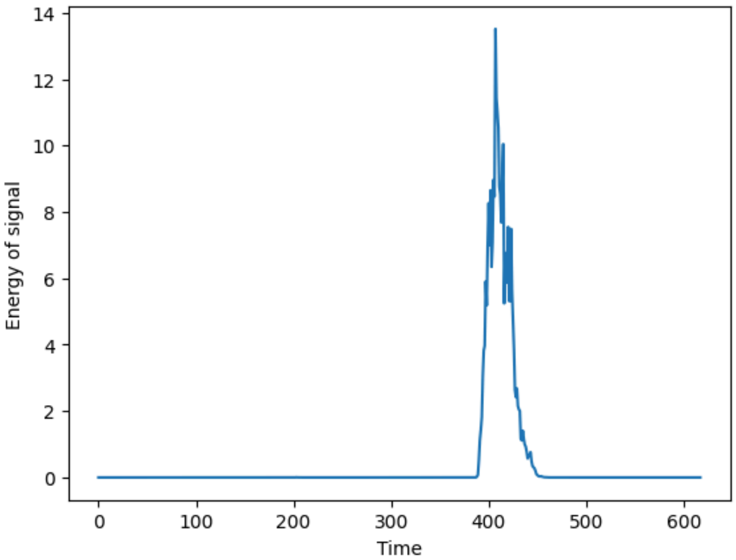

```
Computing MFCC features

 DTW

Min distance matching

Output

2
____________________________________________________
Actual Label :  1
Reading WAV file   /content/drive/MyDrive/test/1t.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

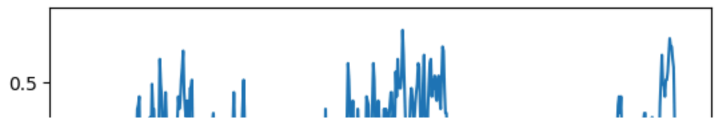


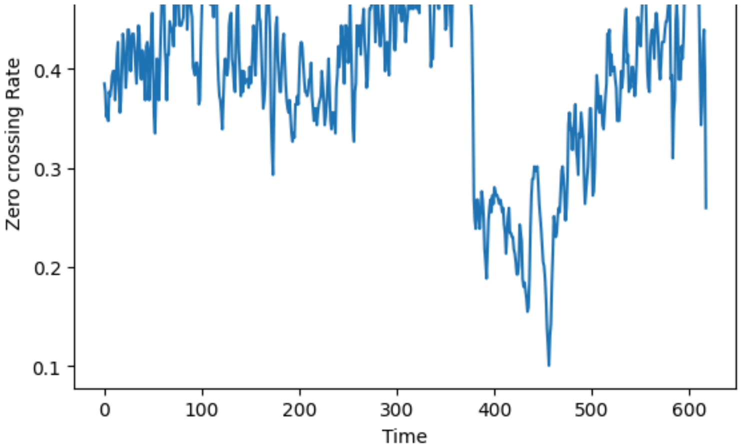




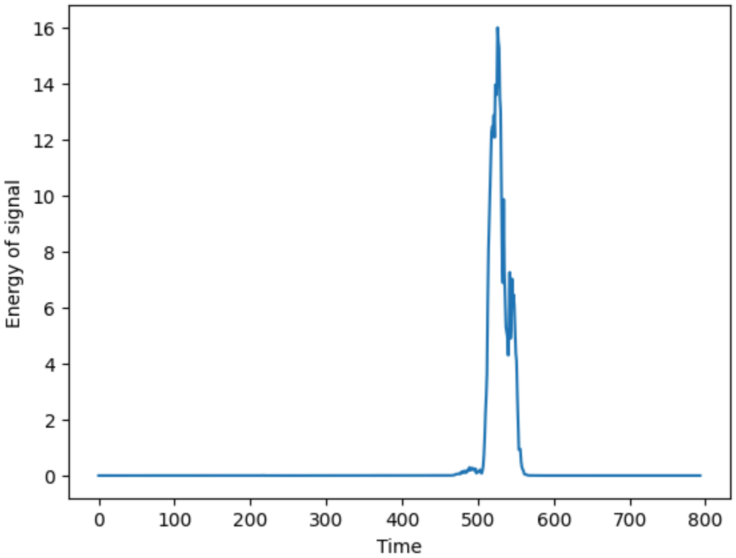

```
Computing MFCC features

 DTW

Min distance matching

Output

1
________________________________________________________
Actual Label :  0
Reading WAV file   /content/drive/MyDrive/test/0t.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```

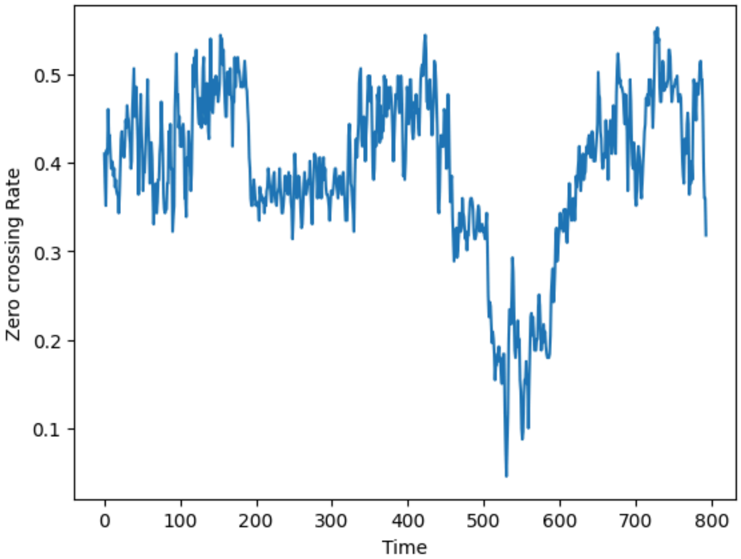







```
Computing MFCC features

 DTW

Min distance matching

Output

0
___________________________________________________
Actual Label :  4
Reading WAV file   /content/drive/MyDrive/test/4t.wav ---

Pre emphasis

Signal framing and windowing

Extracting active voice
```






```
Computing MFCC features
```