## MP3: Cepstrum and Mel-Frequency Cepstrum

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### 1. Introduction

In this mp, we are using raw sound data, frequency cepstrum and MFCC as features to solve the problem. In our case, frequency cepstrum and MFCC is more useful than raw sound data because frequency cepstrum and MFCC can give us better results than raw data and can actually achieve that by using smaller amount of data.

In this mp, we are using the knn classifier to classify the sound data. The algorithm requires calculating the euclidean distance between the test data and each training data, and find the training data that have lowest distance to the the test data and classify the test data as the same class as the training data.

### 2. Methods

For raw data, we just reshape each sound data to a column and return the vector as the feature of each .wav file. This part is implemented at line 26 in run.m file

The part to calculate the frequency cepstrum is implemented in the cepstrum.m file. After pre-emphasizing raw data, the cepstrum was calculated by first set the signal to overlapping frames and windowing each frame. Then, do inverse fft to the log of fft of each frame as the following.

$$c[n] = F^{-1}(log(|F(x[n])|))$$

The last step is to choose the first Ncc = 12 coefficients and unroll the output to a single column vector.

The part of calculate the MFCC is implement in the mfcc.c file. The first step is to pre-emphasize signal and convert resulting signal to overlapping frames. Then we need to compute the Mel Filterbank Weights, H using the melfilterbank(M,K,R,Fs) provided in the melfilterbank.m file. Then we need to compute the Average Magitude Spectrum for each Frame and save the result in matrix X. The next step is to apply H on X to get the Mel magnitudes Y. Then we need to do an inverse discrete cosine transform to the log of Y as

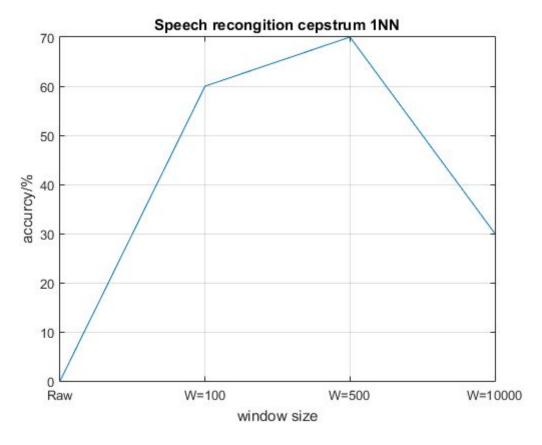
$$c[n] = dct^{-1}(log(Y[n]))$$

The final step is to choose the first Ncc = 12 coefficients and unroll the output to a single column vector.

### 3. Results

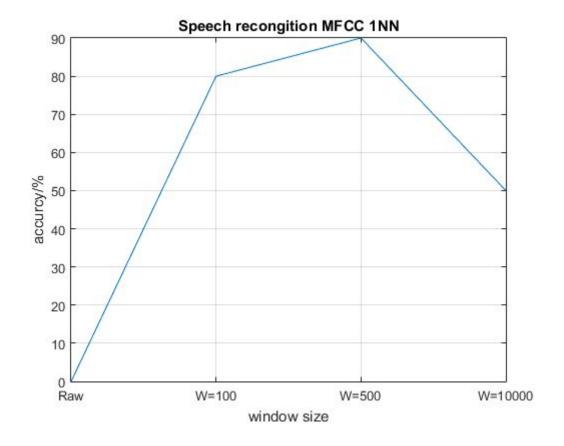
Cepstrum
Speech Recognition
1NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| D1  | 0       | 70.0000 | 65.0000 | 20.0000 |
| D2  | 30.0000 | 45.0000 | 50.0000 | 70.0000 |
| D3  | 15.0000 | 70.0000 | 65.0000 | 70.0000 |
| D4  | 50.0000 | 70.0000 | 65.0000 | 65.0000 |
| D5  | 0       | 60.0000 | 70.0000 | 30.0000 |
| AVG | 19.0000 | 63.0000 | 63.0000 | 51.0000 |



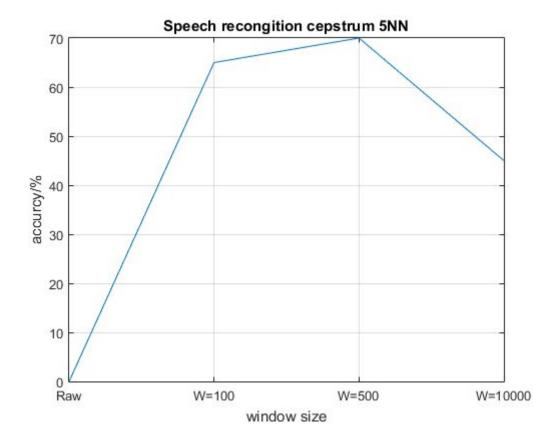
## MFCC Speech Recognition 1NN

|     | Raw     | W =100  | W=500    | W=10000 |
|-----|---------|---------|----------|---------|
| D1  | 0       | 55.0000 | 60.0000  | 35.0000 |
| D2  | 30.0000 | 65.0000 | 90.0000  | 90.0000 |
| D3  | 15.0000 | 95.0000 | 100.0000 | 90.0000 |
| D4  | 50.0000 | 75.0000 | 75.0000  | 60.0000 |
| D5  | 0       | 80.0000 | 90.0000  | 50.0000 |
| AVG | 19.0000 | 74.0000 | 83.0000  | 65.0000 |



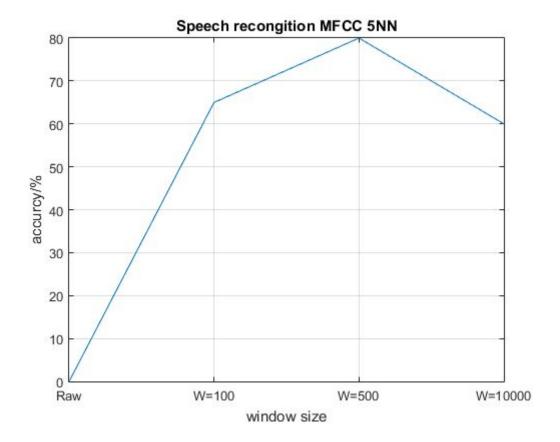
# Cepstrum Speech Recognition 5NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| D1  | 0       | 85.0000 | 65.0000 | 25.0000 |
| D2  | 45.0000 | 45.0000 | 55.0000 | 55.0000 |
| D3  | 5.0000  | 60.0000 | 65.0000 | 60.0000 |
| D4  | 30.0000 | 55.0000 | 55.0000 | 55.0000 |
| D5  | 0       | 65.0000 | 70.0000 | 45.0000 |
| AVG | 16.0000 | 62.0000 | 62.0000 | 48.0000 |



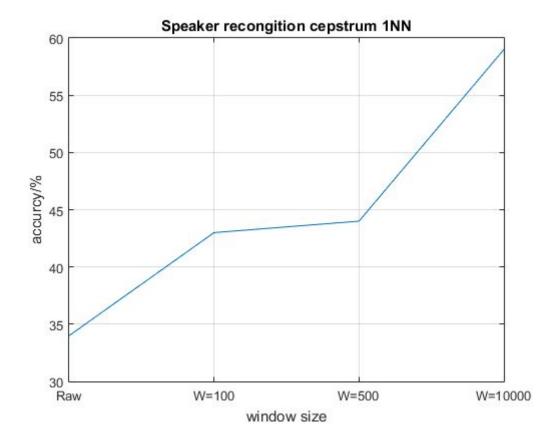
MFCC Speech Recognition 5NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| D1  | 0       | 85.0000 | 70.0000 | 30.0000 |
| D2  | 45.0000 | 65.0000 | 90.0000 | 80.0000 |
| D3  | 5.0000  | 90.0000 | 95.0000 | 85.0000 |
| D4  | 30.0000 | 50.0000 | 65.0000 | 60.0000 |
| D5  | 0       | 65.0000 | 80.0000 | 60.0000 |
| AVG | 16.0000 | 71.0000 | 80.0000 | 63.0000 |



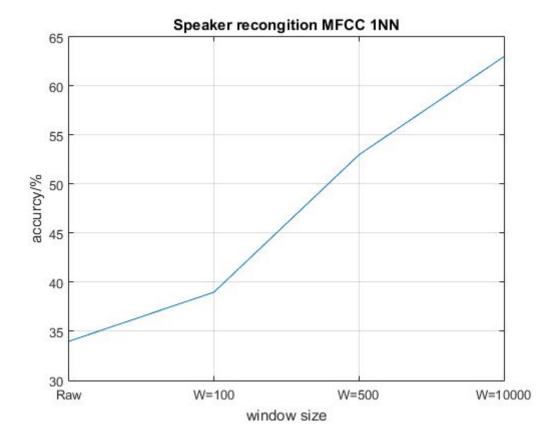
## Cepstrum Speaker Recognition 1NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| P1  | 8.0000  | 52.0000 | 60.0000 | 56.0000 |
| P2  | 76.0000 | 60.0000 | 52.0000 | 88.0000 |
| P3  | 36.0000 | 20.0000 | 32.0000 | 52.0000 |
| P4  | 16.0000 | 40.0000 | 32.0000 | 40.0000 |
| AVG | 34.0000 | 43.0000 | 44.0000 | 59.0000 |



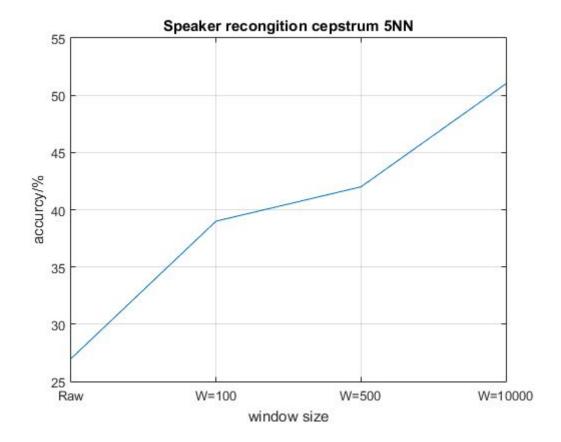
MFCC Speaker Recognition 1NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| P1  | 8.0000  | 40.0000 | 60.0000 | 56.0000 |
| P2  | 76.0000 | 60.0000 | 84.0000 | 76.0000 |
| P3  | 36.0000 | 40.0000 | 36.0000 | 64.0000 |
| P4  | 16.0000 | 16.0000 | 32.0000 | 56.0000 |
| AVG | 34.0000 | 39.0000 | 53.0000 | 63.0000 |



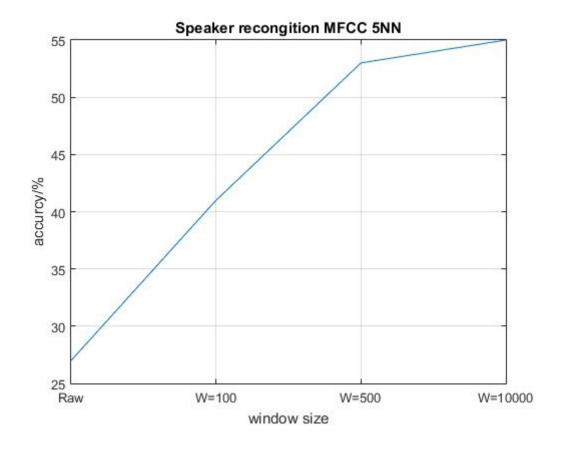
## Cepstrum Speaker Recognition 5NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| P1  | 8.0000  | 52.0000 | 68.0000 | 52.0000 |
| P2  | 92.0000 | 56.0000 | 72.0000 | 76.0000 |
| P3  | 8.0000  | 16.0000 | 8.0000  | 44.0000 |
| P4  | 0       | 32.0000 | 20.0000 | 32.0000 |
| AVG | 27.0000 | 39.0000 | 42.0000 | 51.0000 |



MFCC Speaker Recognition 5NN

|     | Raw     | W=100   | W=500   | W=10000 |
|-----|---------|---------|---------|---------|
| P1  | 8.0000  | 60.0000 | 68.0000 | 60.0000 |
| P2  | 92.0000 | 56.0000 | 80.0000 | 80.0000 |
| P3  | 8.0000  | 32.0000 | 44.0000 | 40.0000 |
| P4  | 0       | 16.0000 | 20.0000 | 40.0000 |
| AVG | 27.0000 | 41.0000 | 53.0000 | 55.0000 |



### 4. Discussion

An interesting result from the experiment data above is that, contrasting to what people think that raw feature can always provide best classify result, in this case the raw data actually give us the worst classify result. In general, on one hand, the MFCC can give us better result than cepstrum and the 5nn classifier always offers us worse result than 1nn classifier in any features extraction methods in either speaker recognition and speech recognition. On the other hand, in speech recognition, window size of 500 samples will create the best estimating result among three but in speaker recognition, it is the window size of 10000 samples that did it.