SPEECH RECOGNITION USING DYNAMIC TIME WARPING

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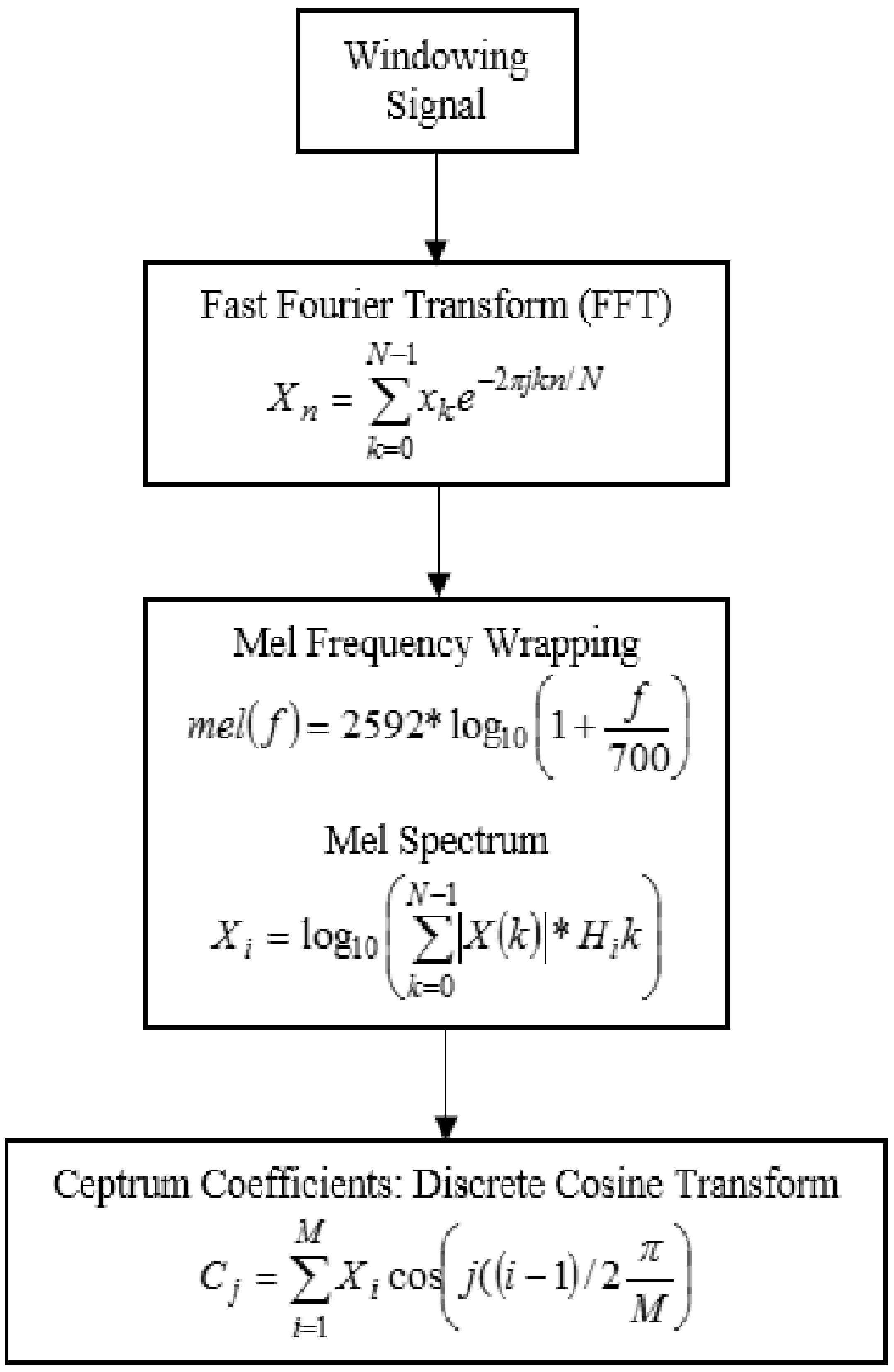
In [22]:
```
import numpy as np
from scipy.spatial.distance import euclidean
from fastdtw import fastdtw
import pandas as pd
import matplotlib.pyplot as plt
from python_speech_features import mfcc
```

INTRODUCTION

Voice commands can be given to drive or actuate a system. Speech recognition is the primary requirement for the said task. Speech recognition is ability of a machine or A program to identify words and phrases in spoken language and convert them into a machine-readable format.The recognition process involves processing of the input command and the library commands and then matching them by using a suitable matching algorithm.

In [1]:
```
def simulate(amplitude_1,frequency_1,amplitude_2,frequency_2,samples):

    x = np.arange(samples)

    signal_1 = amplitude_1 * np.sin(2 * np.pi * frequency_1 * x/44100)
    signal_2 = amplitude_2 * np.sin(2 * np.pi * frequency_2 * x/44100)

    return (signal_1, signal_2)
```

For prototyping this proof-of-concept, we use simulated signals instead of real ones. The simulation includes signals with varying amplitudes and frequencies. The first step in feature engineering is to compute MFCC of the data. MFCC takes into account human perception for sensitivity at appropriate frequencies by converting the conventional frequency to Mel Scale, and are thus suitable for speech recognition tasks quite well. Below are the steps on how to compute MFCC -


Windowing Signal
Fast Fourier Transform (FFT)
$X_n = \sum_{k=0}^{N-1} x_k e^{-2\pi jkn/N}$
Mel Frequency Wrapping
$mel(f) = 2592 * \log_{10}\left(1 + \frac{f}{700}\right)$
Mel Spectrum
$X_i = \log_{10}\left(\sum_{k=0}^{N-1} |X(k)| * H_i k\right)$
Ceptrum Coefficients: Discrete Cosine Transform
$C_j = \sum_{i=1}^{M} X_i \cos\left(j((i-1)/2\frac{\pi}{M}\right)$

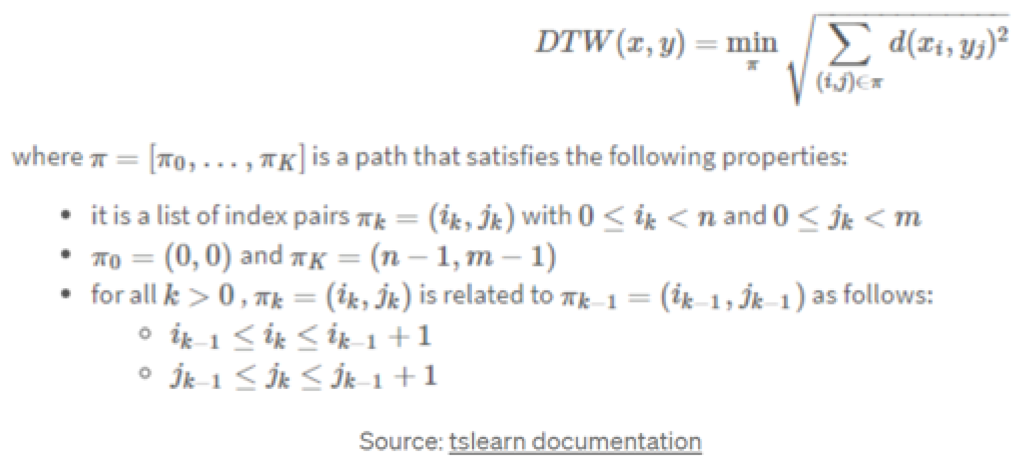
Source:Semanticscholar.org

In [79]:
```
def similarity(series1,series2):

    mfcc1 = mfcc(series1)
    mfcc2 = mfcc(series2)

    distance, path = fastdtw(mfcc1, mfcc2, dist=euclidean)

    return distance

def similar_series(z):

    closest = []

    for i in range(10,101,10):
        value = z[i-10:i].sort_values(by = 0, ascending = True)[1:2].index[0]
        closest.append(value)

    for k in range(0,10,1):

        if closest[k] < 10:
            print(closest[k])
        else:
            print(str(closest[k])[0] + '-->' + str(closest[k])[1])
```

DYNAMIC TIME WARPING

We utilise this method for matching the feature engineered mfcc data points. it is widely used in comparing and evaluating temporal data. It works by first evaluating the least cost distance to reach every square in the grid and then tracing back the path which corresponds to the overall least cost distance.

Below is the algorithm in a nutshell:



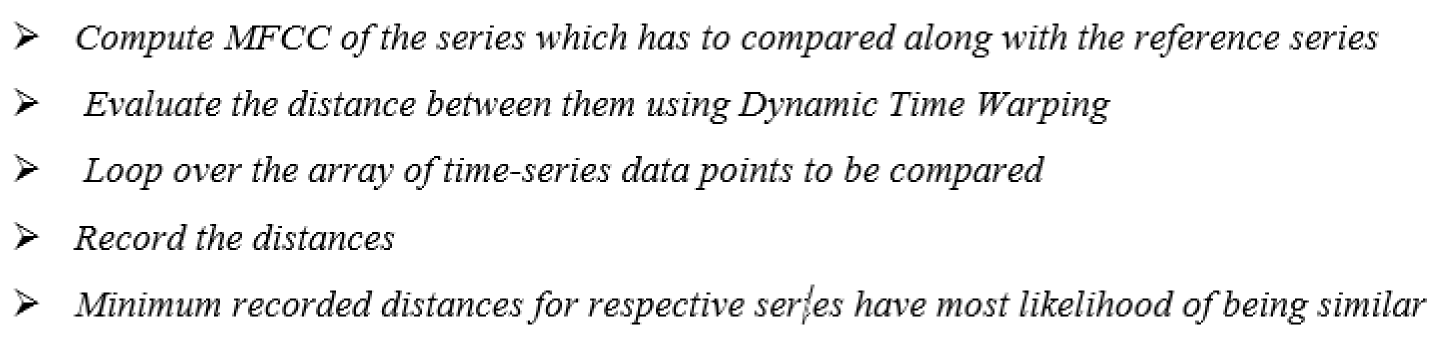
$$DTW(x, y) = \min_{\pi} \sqrt{\sum_{(i,j)\in\pi} d(x_i, y_j)^2}$$

where $\pi = [\pi_0, \ldots, \pi_K]$ is a path that satisfies the following properties:

- it is a list of index pairs $\pi_k = (i_k, j_k)$ with $0 \le i_k < n$ and $0 \le j_k < m$
- $\pi_0 = (0, 0)$ and $\pi_K = (n-1, m-1)$
- for all $k > 0$, $\pi_k = (i_k, j_k)$ is related to $\pi_{k-1} = (i_{k-1}, j_{k-1})$ as follows:
  - $i_{k-1} \le i_k \le i_{k-1} + 1$
  - $j_{k-1} \le j_k \le j_{k-1} + 1$

Source: tslearn documentation

PROOF OF CONCEPT - DYNAMIC TIME WARPING IN CONJUCTION WITH MFCC



- *Compute MFCC of the series which has to compared along with the reference series*
- *Evaluate the distance between them using Dynamic Time Warping*
- *Loop over the array of time-series data points to be compared*
- *Record the distances*
- *Minimum recorded distances for respective series have most likelihood of being similar*

In [81]:
```
def check_series():

    no_of_series = 10
    freq = []
    amplitude = []
    sim = []

    for i in range(0,no_of_series,1):
        freq.append(np.random.randint(5,10))
        amplitude.append(np.random.randint(20,80))

    for i in range(0,no_of_series,1):
        for j in range(0,no_of_series,1):
            x = simulate(freq[i],amplitude[i],freq[j],amplitude[j],100)
            sim.append(similarity(x[0],x[1]))

    return similar_series(pd.DataFrame(sim))

check_series()
```

```
1
1-->3
2-->6
3-->1
4-->3
5-->6
6-->5
7-->9
8-->6
9-->7
```

REFERENCES

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