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Advancements in Speaker Recognition: Exploring Mel Frequency Cepstral Coefficients (MFCC) for Enhanced Performance in Speaker Recognition

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Abstract: ***Speaker recognition, a fundamental capability of software or hardware systems, involves receiving speech signals, identifying the speaker present in the speech signal, and subsequently recognizing the speaker for future interactions. This process emulates the cognitive task performed by the human brain. At its core, speaker recognition begins with speech as the input to the system. Various techniques have been developed for speech recognition, including Mel frequency cepstral coefficients (MFCC), Linear Prediction Coefficients (LPC), Linear Prediction Cepstral coefficients (LPCC), Line Spectral Frequencies (LSF), Discrete Wavelet Transform (DWT), and Perceptual Linear Prediction (PLP). Although LPC and several other techniques have been explored, they are often deemed impractical for real-time applications. In contrast, MFCC stands out as one of the most prominent and widely used techniques for speaker recognition. The utilization of cepstrum allows for the computation of resemblance between two cepstral feature vectors, making it an effective tool in this domain. In comparison to LPC-derived cepstrum features, the use of MFCC features has demonstrated superior performance in metrics such as False Acceptance Rate (FAR) and False Rejection Rate (FRR) for speaker recognition systems. MFCCs leverage the human ear's critical bandwidth fluctuations with respect to frequency. To capture phonetically important characteristics of speech signals, filters are linearly separated at low frequencies and logarithmically separated at high frequencies. This design choice is central to the effectiveness of the MFCC technique. The primary objective of the proposed work is to devise efficient techniques that extract pertinent information related to the speaker, thereby enhancing the overall performance of the speaker recognition system. By optimizing feature extraction methods, this research aims to contribute to the advancement of speaker recognition technology.***

Keywords: Speech recognition, Mel frequency cepstral coefficients (MFCC), Feature extraction, Speech signal processing, Speaker identification, Cognitive computing.

I. INTRODUCTION

Human speech is a fundamental means by which individuals convey their emotions, opinions, thoughts, and ideas orally. The process of speech production involves intricate coordination of articulation, voice generation, and fluency [1]. This natural motor ability, observed in regular adults, allows for the production of approximately 14 distinct speech sounds per second, facilitated by a harmonized network of around 100 muscles interconnected through spinal and cranial nerves [2]. Despite the apparent ease with which humans speak, the underlying complexity of this task makes speech highly sensitive to diseases associated with the nervous system, which might offer insights into related pathologies [3]. To improve speaker recognition systems, researchers, such as Xinhui Zhou and Garcia Romero (2012), have explored the comparison of Linear Frequency Cepstral Coefficients (LFCC) and Mel Frequency Cepstral Coefficients (MFCC) [4]. Their investigation was guided by observations from speech production, suggesting that certain speaker characteristics, particularly those related to the vocal tract structure, are more prominent in the high-frequency region of speech [5][6]. Analysis of MFCC and LFCC performances in the NIST SRE 2010 extended core task revealed that while these techniques complement each other, LFCC consistently outperforms MFCC, especially in female trials, owing to its ability to capture spectral characteristics in the high-frequency range [7][8][9]. While both methods exhibit resilience against babble noise, LFCC's performance differs from MFCCs when dealing with white noise [10][11].

In the pursuit of robust feature extraction from MFCC techniques, Sahidullah and Saha proposed the 'Differentiation in frequency domain' approach in 2013, modifying the Hamming window technique to obtain the derivative of Fourier transform [12]. Among the existing techniques for speaker extraction, MFCC remains one of the most well-known and widely used methods[13]. The utilization of cepstrum allows for the computation of resemblance between two cepstral feature vectors [14].

This paper comprehensively explores the intricacies of human speech production and investigates the comparative efficacy of MFCC in the domain of speaker recognition. The findings contribute to a deeper understanding of speech-related mechanisms and offer potential implications for advancing speaker recognition technologies.

II. SYSTEM DESCRIPTION

A. *Block Diagram of MFCC*

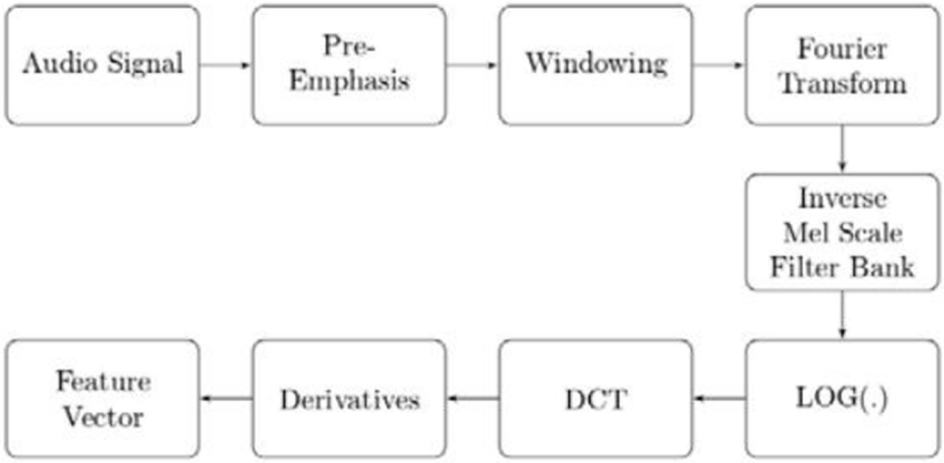

Fig 1.

B. *Pre-emphasis*

Pre-emphasis is performed to enhance the higher frequencies of the spectrum. Pre-emphasis flattens the signal making it less susceptible to finite precision.

C. *Framing*

The speech signal exhibits quasi-periodic characteristics, displaying a repetitive pattern over time. To effectively analyze the speech signal, it is divided into several frames, each lasting approximately 20 to 30 milliseconds. Within each frame, the speech signal is considered to be stationary, facilitating meaningful analysis. In order to ensure a comprehensive examination without loss of crucial information, a 50% overlap is applied between successive frames [16].

D. *Windowing*

Windowing involves the slicing of the audio waveform into sliding frames. let, w is the window applied to the original audio clip in the time domain. x[n]=w[n]s[n]
Here, w[n] is a sliced frame whereas s[n] is an original audio clip.
The corresponding equations for w are:

$$w[n] = (1-\alpha) - \alpha\cos\left(\frac{2\pi n}{L-1}\right)$$

L = window width

Hamming(α=0.46164) or Hanning(α=0.5) window.

E. *FFT*

The frequency content of the windowed signal is estimated using the Fast Fourier Transform (FFT), which facilitates the conversion of each frame from the time domain to the frequency domain. This process allows for the computation of the short-term frequency content of the signal through the application of FFT on individual frames. Subsequently, the power spectrum is computed by evaluating the squared magnitude of the windowed signal.

F. Mel-Filter Bank

The windowed signal is multiplied with a mel-filter bank. The Mel scale is an auditory scale similar to the frequency scale of the human ear (similar to how the human ear perceives sound). The scale is roughly linear below 1 kHz and logarithmic above 1 kHz. The relationship between linear frequency and mel scale is given by following formula:

$$m = 2595 \log_{10}\left(1 + \frac{f}{700}\right) = 1127 \ln\left(1 + \frac{f}{700}\right)$$

G. DCT

In the last step, logarithm operation is performed followed by discrete cosine transform to de-correlate the log energies. The DCT compresses the signal. The cepstrum is calculated using discrete cosine transform(DCT) or inverse Fourier transform to obtain MFCCs [16].

H. Correlation Technique

Syntax for cross correlation: r=xcorr(x,y) Correlation is a measure of similarity of two series as a function of the displacement of one relative to the other. This is also known as a sliding dot product or sliding inner product [17].

III. RESULTS

A. Input Audio signals

- *Voice 1*

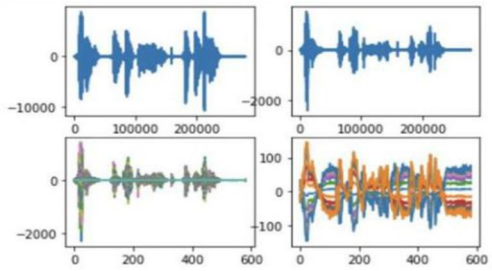

Fig 2.

- *Voice 2*

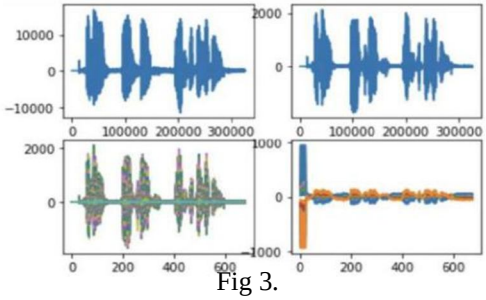

Fig 3.

- *Voice 3*

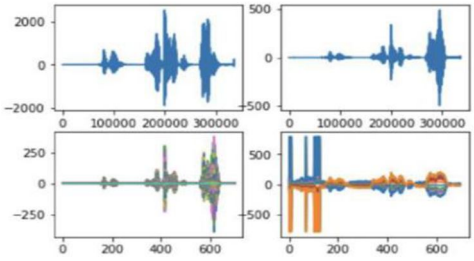

Fig 4.

- *Voice 4*

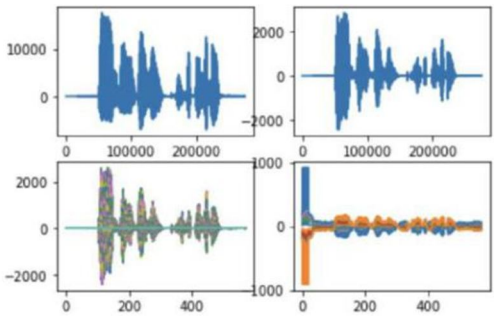

Fig 5.

1) Voice 1 is set as Input voice

Correlation of Voice 1 in database with input voice

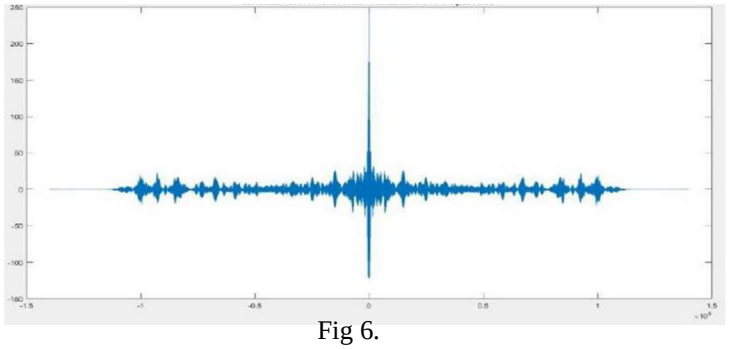

Fig 6.

Correlation of Voice 2 in database with input voice

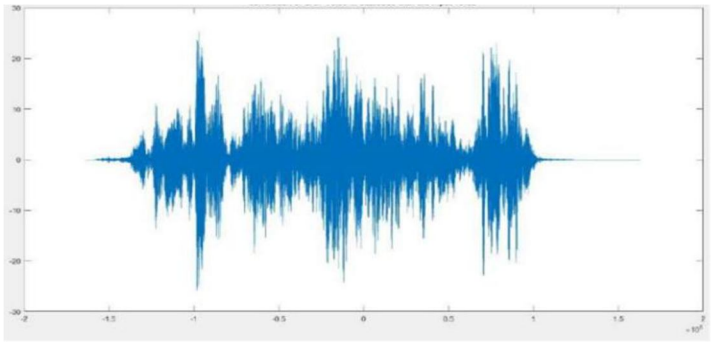

Fig 7.

Correlation of Voice 3 in database with input voice

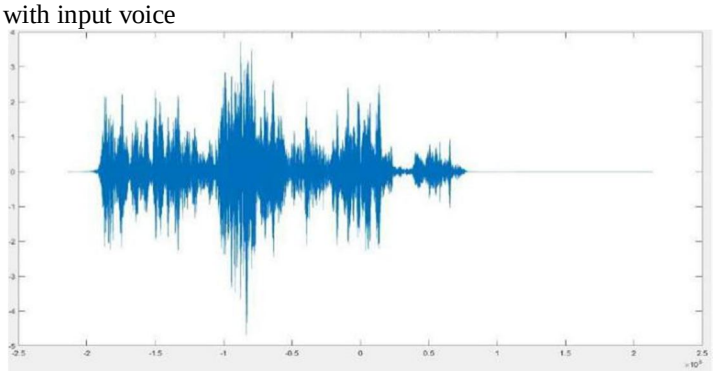

Fig 8.

Correlation of Voice 4 in database with input voice

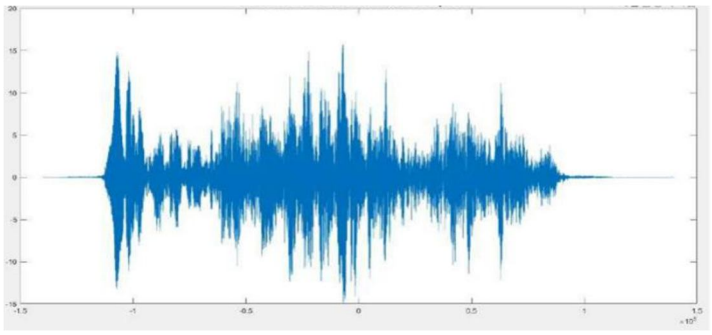

Fig 9.

Peaks

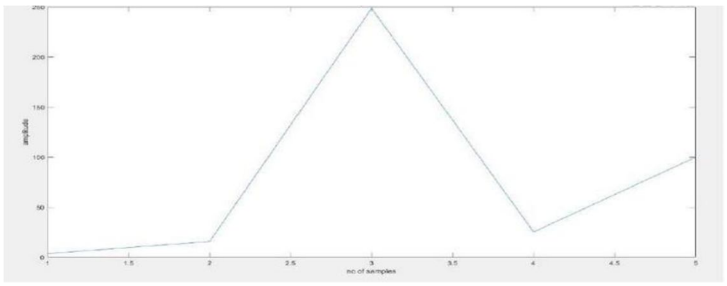

Fig 10.

2) *Voice 2 is set as Input voice :*

Correlation of Voice 1 in database with input voice

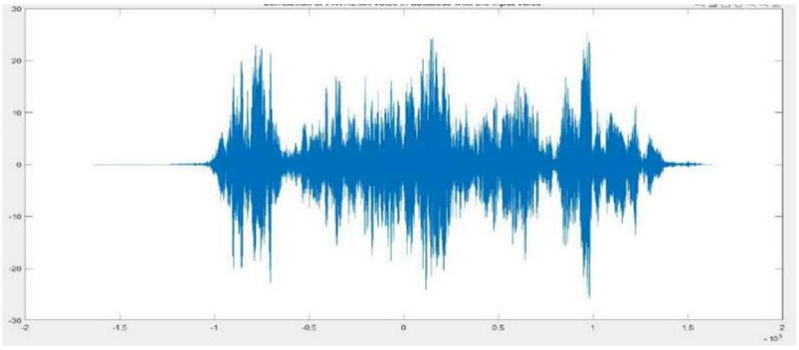

Fig 11.

Correlation of Voice 2 in database with input voice

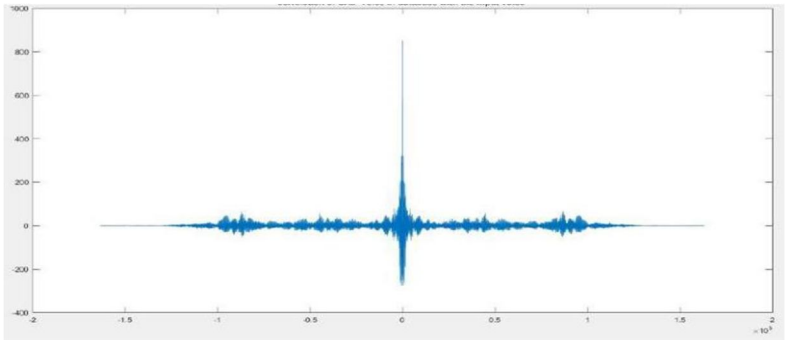

Fig 12.

Correlation of Voice 3 in database with input voice

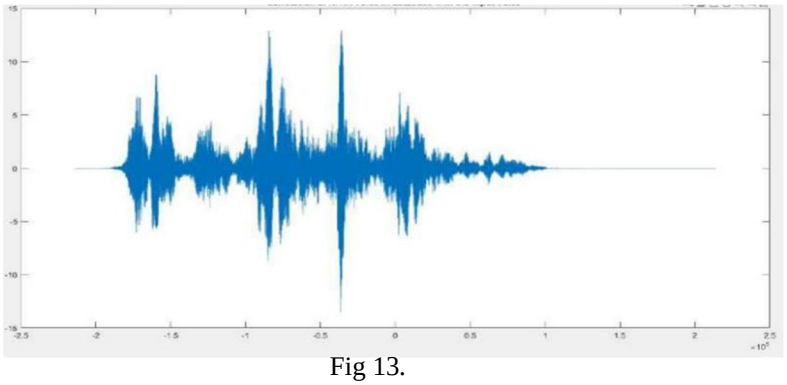

Fig 13.

Correlation of Voice 4 in database with input voice

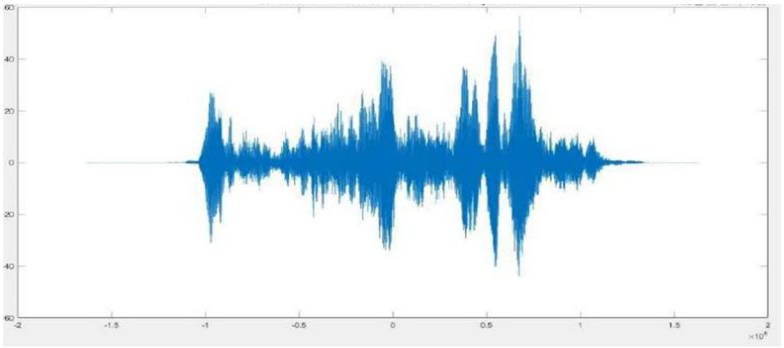

Fig 14.

Peaks

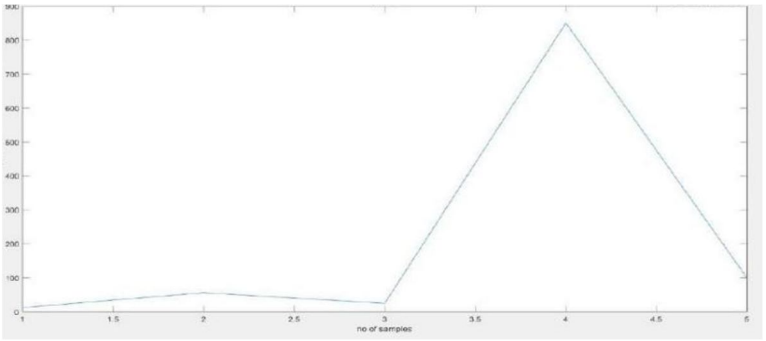

Fig 15.

3) Voice 3 is set as Input voice :

Correlation of Voice 1 in database with input voice

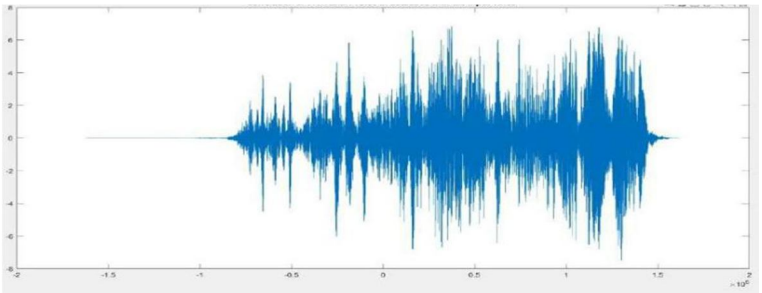

Fig 16.

Correlation of Voice 2 in database with input voice

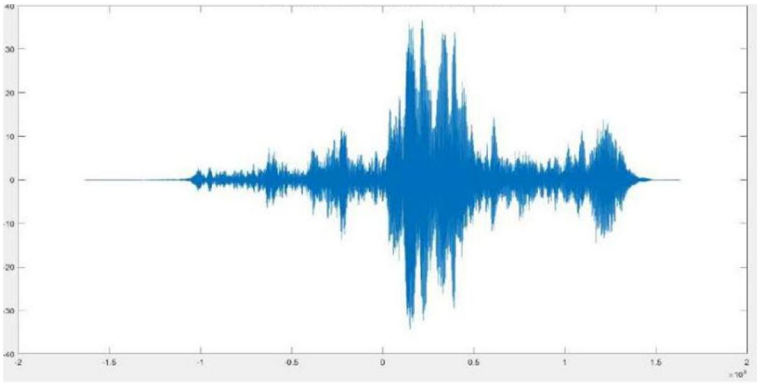

Fig 17.

Correlation of Voice 3 in database with input voice

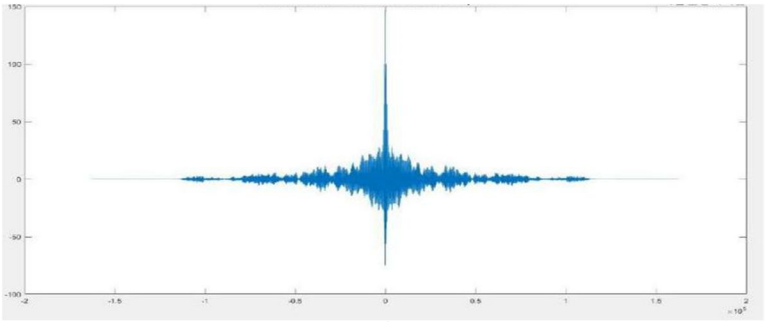

Fig 18.

Correlation of Voice 4 in database with input voice

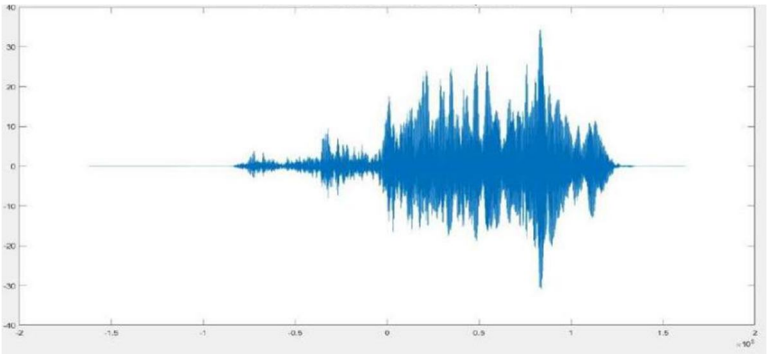

Fig 19.

Peaks

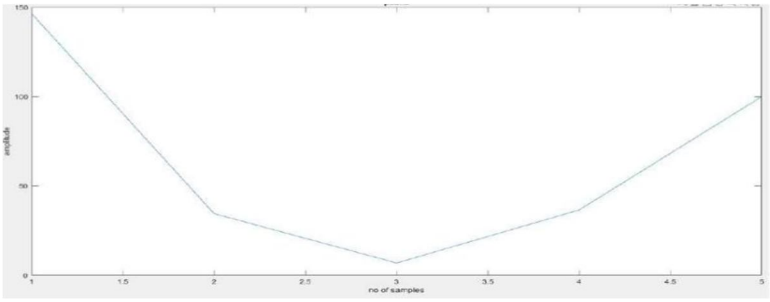

Fig 20.

4) Voice 4 is set as Input Voice

Correlation of Voice 1 in database with input voice

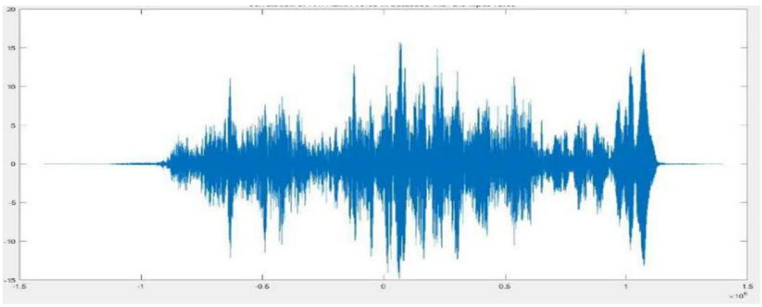

Fig 21.

Correlation of Voice 2 in database with input voice

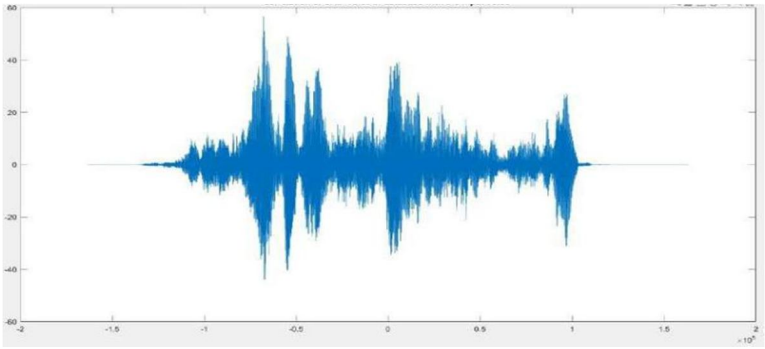

Fig 22.

Correlation of **Voice 3** in database with input voice

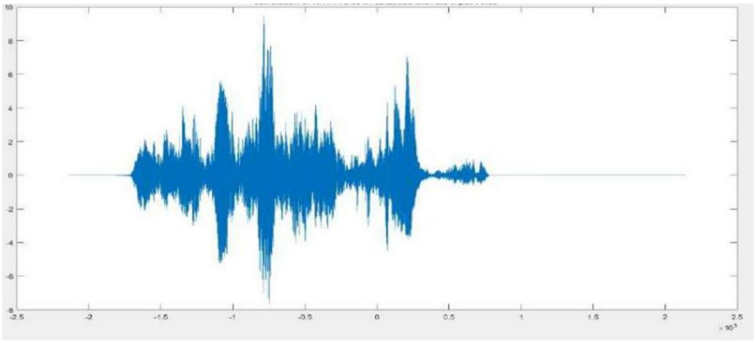

Fig 23.

Correlation of Voice 4 in database with input voice

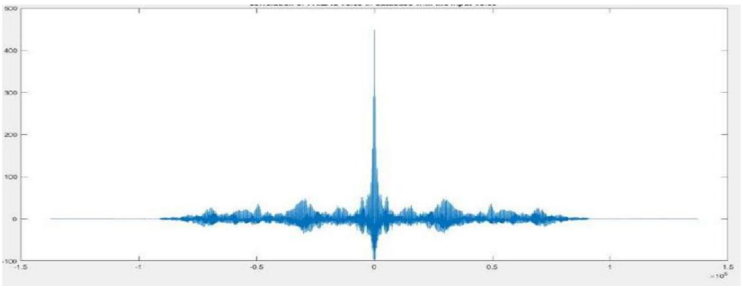

Fig 24.

Peaks

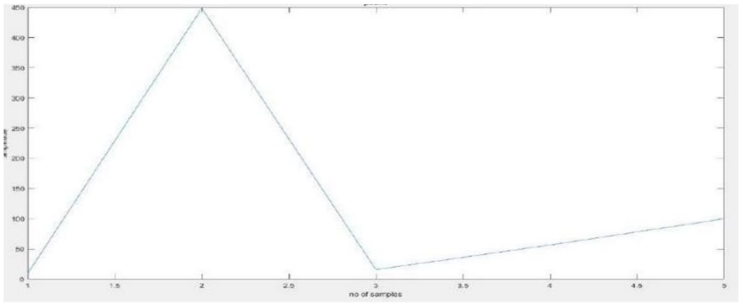

Fig 25.

B. Random Voice Input

Correlation of Voice 1 in database with input voice

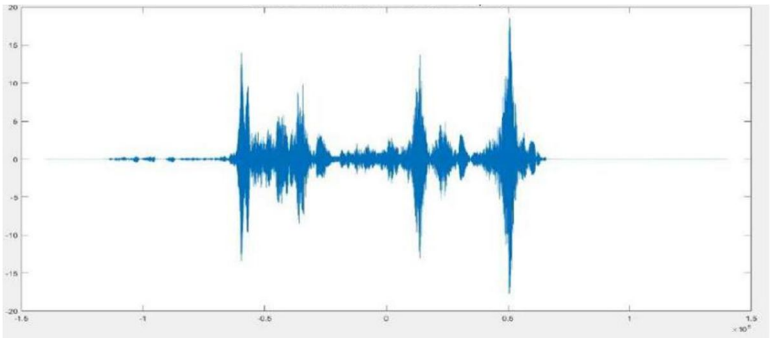

Fig 26.

Correlation of Voice 2 in database with input voice

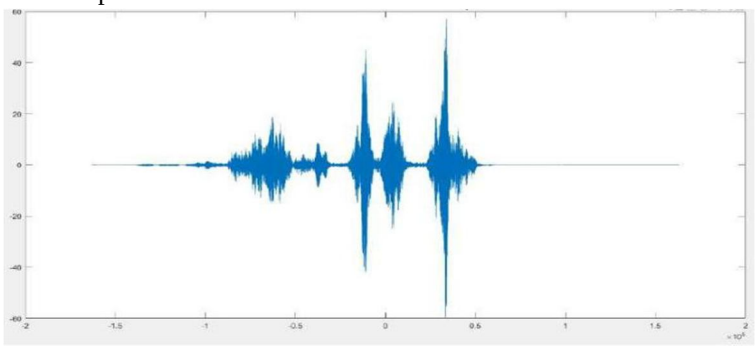

Fig 27.

Correlation of Voice 3 in database with input voice

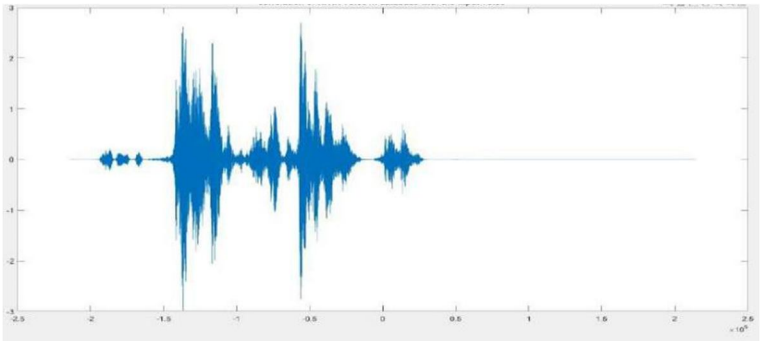

Fig 28.

Correlation of Voice 4 in database with input voice

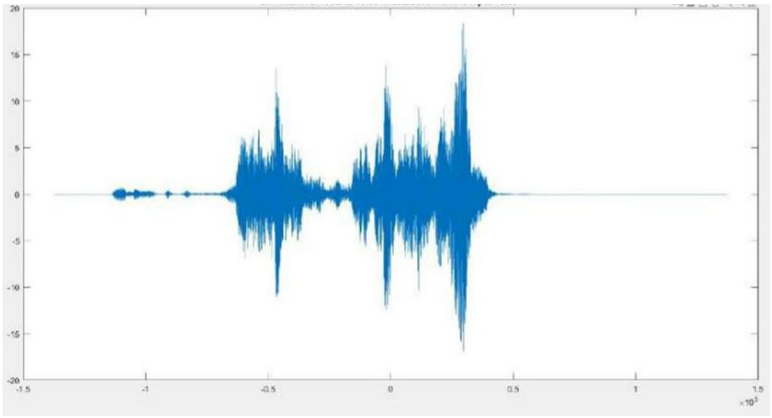

Fig 29.

Peaks

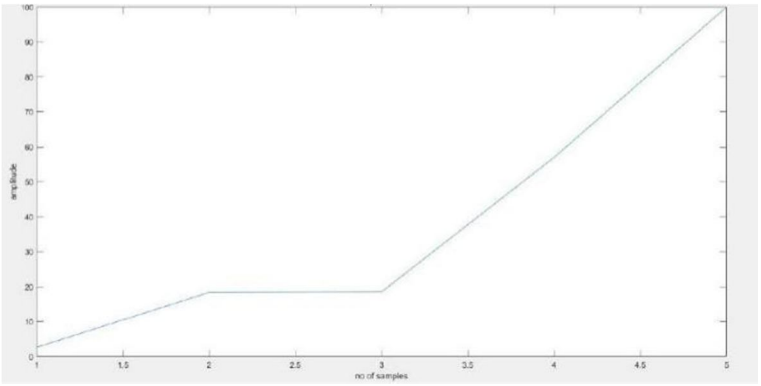

Fig 30

IV. CONCLUSION

We have reviewed feature extraction technique Mel-Frequency Cepstral Coefficients (MFCCs) for speaker recognition. The factor's channel mismatch, background noise affects the performance of MFCC technique. The scheme for robust feature extraction is necessary. Speech signals are extracted by using MFCC technique where features are extracted using linearly spaced filters in Mel scale. Compared to other existing techniques, this method of MFCC provides the beer feature extraction. The weighted vector quantization is suitable for 2D acoustic signals, leading to higher material recognition accuracy than that of other systems. Correlation process is also a nice upon for speech recognition but it's not accurate as of the MFCC process. The whole process of speech recognition using correlation methods has been explained by our project. Application of methods explained above. These methods can be used for security purposes of door unlocking using speech recognition.

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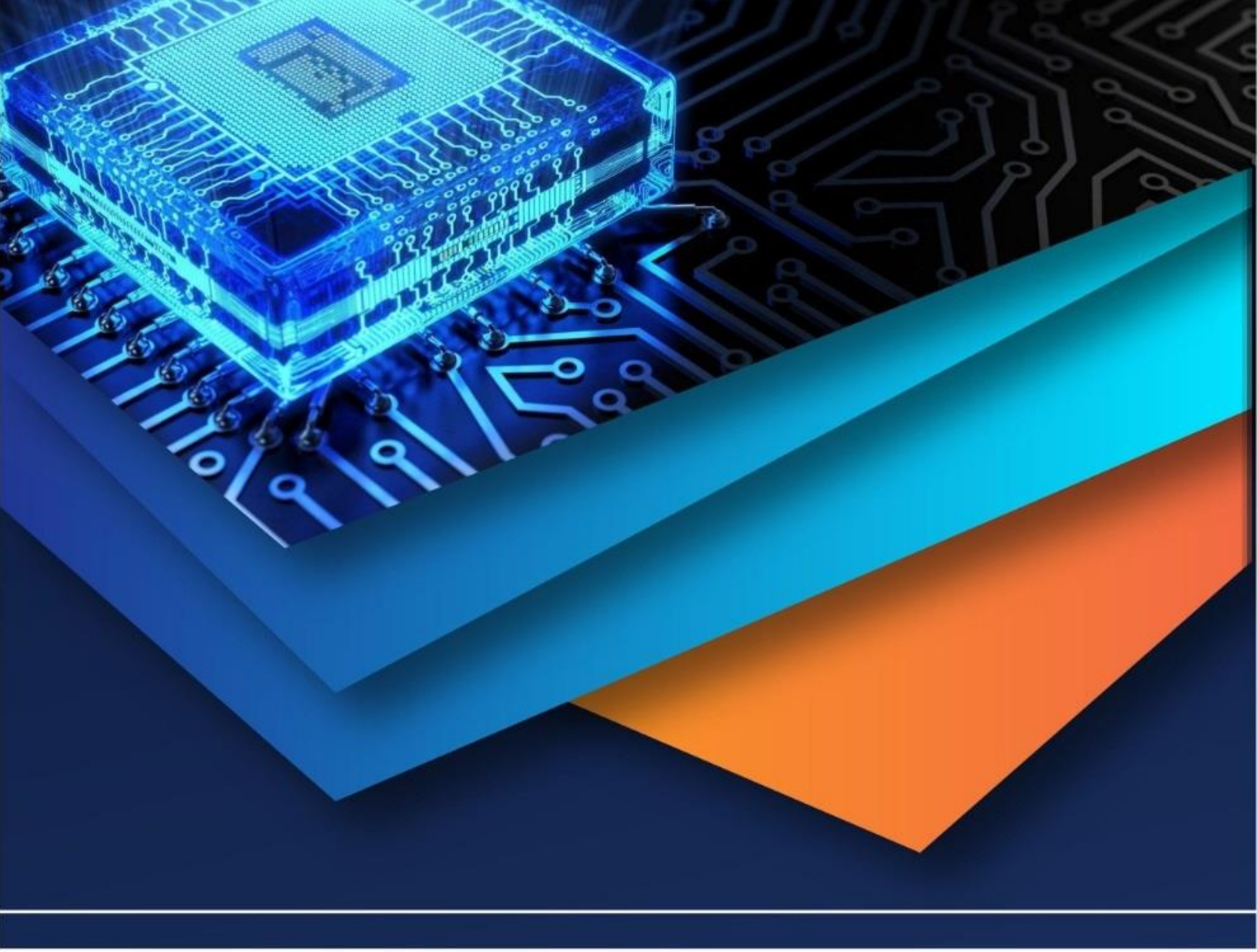

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