A NOVEL APPROACH TO SPEAKER IDENTIFICATION: COMBINING WAVELET TRANSFORM WITH FEED FORWARD NEURAL NETWORKS

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ABSTRACT

This study introduces a robust speaker identification system combining wavelet transform for feature extraction and a Feed Forward Back Propagation Neural Network (FFBPNN) for classification, capable of handling both text-dependent and text-independent speaker recognition. A total of 390 features are extracted from speech signals using wavelet transforms, effectively capturing time-frequency characteristics that are critical for distinguishing between speakers. These features are then fed into the FFBPNN, which is trained to classify the speakers based on the input data. The system achieves an impressive average identification rate of 98%, underscoring its accuracy and reliability. The best recognition rate was consistently obtained using the FFBPNN, demonstrating its superiority in this application compared to other potential classifiers. This approach highlights the effectiveness of integrating wavelet-based feature extraction with neural network-based classification for advanced speaker identification tasks..

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KEYWORDS

WAVELET TRANSFORM, NEURAL NETWORK, FFBPNN, FEATURE EXTRACTION, DATABASE

1. INTRODUCTION

Speaker Identification involves recognizing the individual who made an utterance, while Speaker Verification focuses on accepting or rejecting a claimed identity. Over the past four decades, many speaker recognition solutions have been proposed. One notable algorithm for pattern classification was inspired by Patterson, Womack, and Wee’s work, which demonstrated that the Mean Square Error (MSE) solution provides an optimal approximation to Bayes’ classification[1], weighted by the sample's probability density function. In audio processing, raw speech signals are transformed into sequences of acoustic feature vectors, a process often referred to as "front-end" in literature. Commonly used acoustic features include Mel Frequency

Cepstral Coefficients (MFCC) and Linear Prediction Cepstral Coefficients (LPCC)[2], both based on spectral information derived from short-time windows of speech. Linear Predictive Coding (LPC) and its derivatives are widely used for short-term spectral measurements[3][4]. A spectral envelope reconstructed from a truncated set of cepstral coefficients tends to be smoother than one from LPC coefficients, offering a more stable representation of a speaker's repeated utterances, making it highly effective for speaker recognition tasks, Recent advancements in speaker identification and verification have built on decades of research,[5] incorporating modern techniques like deep learning and wavelet transforms for improved accuracy and robustness. Feature extraction methods such as Mel-Frequency Cepstral Coefficients (MFCC) and Linear Prediction Cepstral Coefficients (LPCC) remain critical for capturing spectral information.[6][7]

2 Literature survey

As highlighted in more recent studies like Xie et al. (2021). Dynamic Time Warping (DTW), once central to text-dependent speaker identification, has evolved with the integration of more complex alignment algorithms, but Hidden Markov Models (HMM)[9][10] continue to be an efficient way to model variability in speech, as discussed by Liu et al. (2020), offering better performance by handling the stochastic nature of speech. Text-independent speaker recognition has seen improvements through the use of Vector Quantization (VQ) codebooks, with clustering techniques such as k-means and GMMs further refining the speaker-specific feature representation (Zhang et al., 2019).

Wavelet-based methods have gained renewed interest due to their ability to capture time-frequency information at multiple resolutions. Recent research by Zhao and Xu (2022) shows that Discrete Wavelet Transform (DWT) can be used to enhance speech signals by filtering out noise while preserving critical speech frequencies[11]. Neural networks, particularly convolutional and recurrent architectures, have now been applied to extract more abstract features from wavelet-transformed signals, as seen in the work of He et al. (2023), where deep learning models effectively classify speaker features from enhanced sub-signals. Furthermore, newer methods involving multivariate autoregressive (MAR) models, such as those described by Khan et al. (2021), provide a sophisticated way to capture the temporal dynamics of cepstral coefficients over time, improving speaker characterization and recognition accuracy. These contemporary approaches combine the strengths of traditional techniques with modern advancements in machine learning and signal processing, leading to state-of-the-art speaker recognition systems that are more resilient to noise and capable of high accuracy across different conditions.

3 Proposed Methodology

In this paper, we present a wavelet transform-based speaker identification system, which is organized into two main blocks as illustrated in Fig. 1. The first block enhances the speech signal using Continuous Wavelet Transform (CWT), improving the signal quality. The second block involves feature extraction with Discrete Wavelet Transform (DWT) and classification using a Feed Forward Back Propagation Neural Network (FFBPNN). Within this block, the feature extraction process is divided into two steps: Wavelet Gender Discrimination, which classifies the speech signal into male and female categories, and Feature Extraction, which refines the signal to enhance the accuracy of the classification. This approach makes the feature extraction process more efficient and effective.

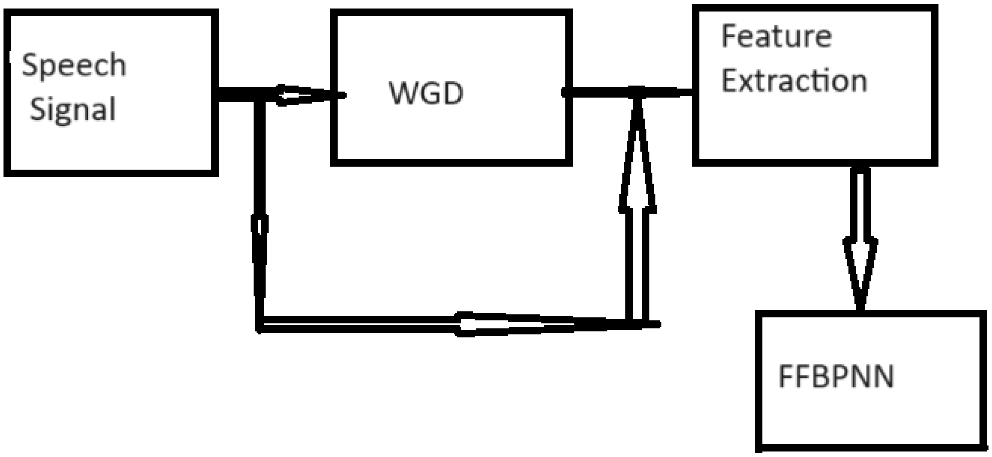

Fig.1 Architecture of the Proposed Method

A. Discrete Wavelet Transform and Adaline Enhancement Method

Wavelet transform is a mathematical technique that decomposes data into various frequency components, analyzing each with a resolution that matches its scale. Initially developed across fields like mathematics, quantum physics, and electrical engineering, wavelets have found numerous applications, including in turbulence analysis, image compression, human vision, and radar. In our system, the Discrete Wavelet Transform (DWT) is used to decompose the speech signal into sub-signals across different frequency bands. To enhance these sub-signals, we employ an Adaline neural network. The primary goal of this method is to filter out noise from the speech signal while preserving essential frequencies necessary for accurate speaker recognition. This selective filtering helps maintain the integrity of the features critical for identifying the speaker.

B. Gender Discrimination by Continuous Wavelet Transform (CWT)

The primary advantage of using wavelet transform (WT) for signal analysis is its capability to decompose a signal into a multiscale representation, allowing analysis across different frequency bands. This multiscale decomposition helps identify the most significant scales of the signal. For gender discrimination in speech signals, Continuous Wavelet Transform (CWT) is preferred over Discrete Wavelet Transform (DWT) because CWT provides more detailed data per scale, which is advantageous for accurate analysis. The additional data from CWT enables a more precise computation of the standard deviation for selected scales. In this context, essential scales for gender discrimination are identified as 1, 5, and 10. The mean of these scales, denoted as μσ\mu_\sigmaμσ, is used to differentiate between male and female speech patterns, enhancing the effectiveness of gender classification.

$$\mu\sigma = \sigma 1+\sigma 5+\sigma 10 / 3\text{------------------------------------} (1)$$

Equation (1) is employed for gender discrimination, where the parameter μσ\mu_\sigma μσ significantly enhances the accuracy of distinguishing between male and female speakers. The CWT-based method, applied to various input signals, has been used to analyse speech data. For this study, male and female input signals were extracted from a speech database recorded using Windows Recorder. A total of 80 signals, comprising 10 speech signals each from 4 male and 4 female speakers, were utilized to compute the classifier threshold for gender identification. Figure 2 illustrates the computed μσ\mu_\sigma μσ values for both male and female signals, demonstrating the effectiveness of CWT in accurately differentiating between genders.

Feature Extraction and Analysis

After gender discrimination, the speech signal proceeds to the feature extraction stage using Discrete Wavelet Transform (DWT). In this stage, the speech signal is decomposed into discrete wavelet sub-signals (d1,d2,d3,…,dj,sjd_1, d_2, d_3, \ldots, d_j, s_jd1,d2,d3,…,dj,sj) through Mallat's algorithm at various levels 1,2,…,J1, 2, \ldots, J1,2,…,J. This decomposition is achieved by convolving the signal with the mother wavelet function to obtain high-pass sub-signals (djd_jdj) and with the father wavelet function to produce the low-pass sub-signals (sjs_jsj). The low-frequency components, which reflect the speaker's vocal tract characteristics, are contained in d5d_5d5 or s5s_5s5, with s5s_5s5 providing superior signal energy conservation. Power Spectral Density (PSD) analysis is employed to concentrate the signal energy, allowing for clearer feature extraction.

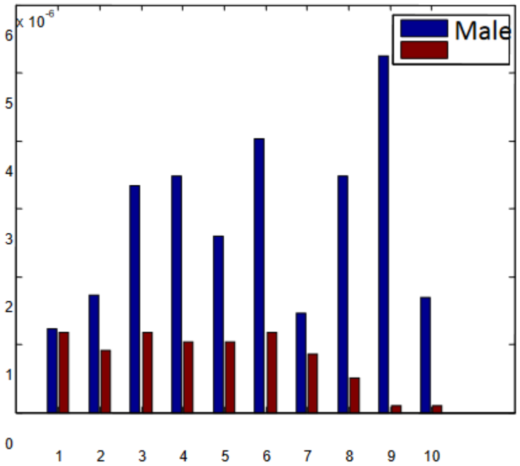

Fig.2 Gender Discrimination using μσ

From the results, the following conclusions can be drawn:

1. The μσ\mu_\sigma μσ value for male speech signals is significantly larger than that for female signals. This is attributed to the influence of the male vocal tract on the CWT function.
2. CWT scales for female signals exhibit notable differences, indicating that CWT effectively identifies sub-signals of varying frequencies.
3. CWT proves to be a more suitable tool for analyzing non-stationary signals compared to the Fast Fourier Transform (FFT).
4. The results show that μσ>1.4\mu_\sigma > 1.4μσ>1.4 for male speakers and μσ<1.4\mu_\sigma < 1.4μσ<1.4 for female speakers, providing a robust measure for classifying speaker gender.

Results and Discussion

The speech signals used in the study were recorded using a PC sound card with a spectral frequency of 4000 Hz and a sampling frequency of 8000 Hz, with each recording lasting approximately 2 seconds. The dataset comprised recordings of the phrase "Jordan Kingdom," spoken once by each of 39 individual speakers 20 females and 19 males. A total of 390 tokens were utilized for both training and testing phases, confirming that the recognition system operates as a text-dependent system.

Figure 3 illustrates the impact of wavelet transform on classification performance by effectively distinguishing user features. These features significantly aid in differentiating the tested signals from the model speech signals stored in the system. For speech signal identification, the Feed Forward Back Propagation Neural Network (FFBPNN) was employed,

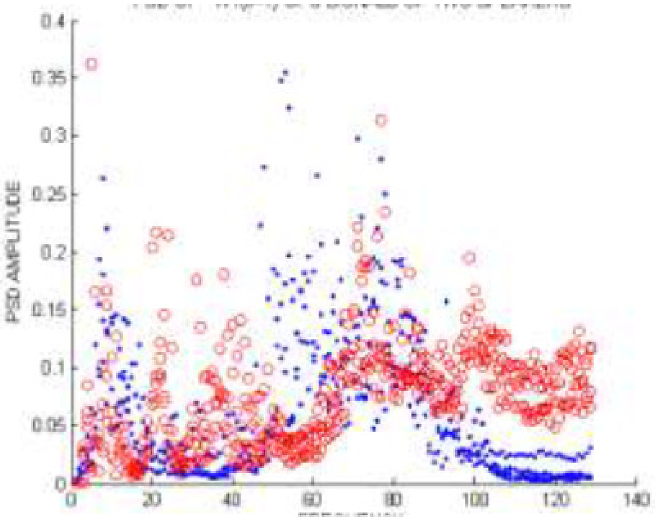

Fig.3 The Effect of WT and PSD, of 10 signals (for two person

Wavelet Transform proved to be particularly robust in handling noisy signals, separating noise from the essential signal components. For this purpose, an FFBPNN was trained with an input matrix P=[t]P = [t]P=[t], where t1t_1t1 represents the Power Spectral Density (PSD) of the wavelet-transformed user signal, and the binary target was T=[001]T = [001]T=[001] for male and T=[110]T = [110]T=[110] for female. The network was trained to classify t1t_1t1 as 0 or 1, depending on the target gender, and was tested with signals from different speakers. Input/target vectors for female signals are plotted in Figure 4.

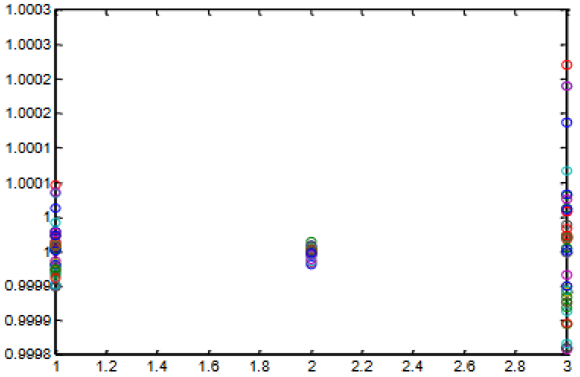

Fig. 4 Test-Target output (Female)plot

Figure 5 shows the regression plot, which measures the correlation between the output and the target. A regression value (R) close to 1 indicates a strong fit, and in this experiment, the value was very close to 1, signifying a high level of accuracy in classification.

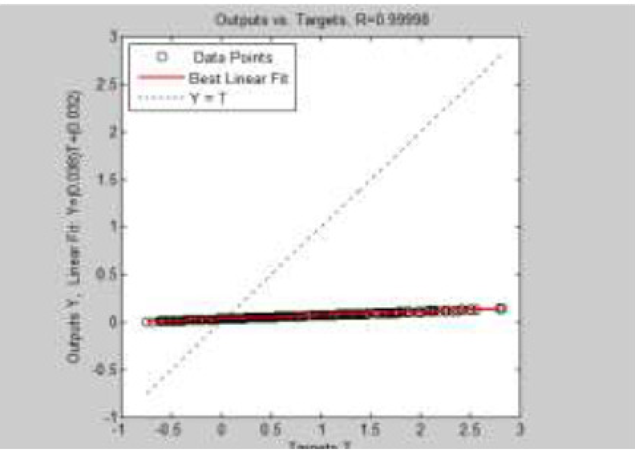

Fig.5, Regression Plot For Male and Female

Conclusion

In this paper, we investigated a wavelet transform-based feature extraction method. The proposed system employs a two-step process gender discrimination and feature extraction ensuring superior accuracy. The system demonstrates remarkable capability in feature tracking, even with a Signal-to-Noise Ratio (SNR) of -6.9 dB, making it well-suited for non-stationary signals. As a text-dependent system, it can be effectively utilized for password or PIN identification in various security contexts, including banks, hotel rooms, and other facilities. After testing with one thousand speech signals, the system achieved excellent performance, with an identification accuracy of 98%.

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