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Online Fault Monitoring of On-Load Tap-Changer Based on Voiceprint Detection

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Abstract

The continuous operation of On-Load Tap-Changers (OLTC) is essential for maintaining stable voltage levels in power transmission and distribution systems. Timely fault detection in OLTC is essential for preventing major failures and ensuring the reliability of the electrical grid. This research paper proposes an innovative approach that combines voiceprint detection using MATLAB analysis for online fault monitoring of OLTC. By leveraging advanced signal processing techniques and machine learning algorithms in MATLAB, the proposed method accurately detects faults in OLTC, providing real-time monitoring and proactive maintenance strategies.

Keywords

Online Fault Monitoring, OLTC, On-Load Tap Change, Voiceprint Detection

1. Introduction

On-Load Tap-Changers (OLTC) play a critical role in regulating voltage levels during varying load conditions in power systems. Traditional methods of fault monitoring for OLTC, like temperature and vibration analysis, have limitations in terms of accuracy and effectiveness. According to (Li Wang and Xiang Dong Liu 2009) [1], the very traditional fault monitoring methods for OLTCs are limited in terms of accuracy and real-time detection capabilities. Therefore, advanced techniques are required to overcome these challenges and provide reliable online monitoring.

Voiceprint detection, a cutting-edge technology in the field of signal processing, has gained substantial attention for various applications, such as speaker identification and speech recognition. In their study, Wang and Liu propose the utilization of voiceprint detection for fault monitoring of OLTCs. By analyzing the acoustic emissions generated during the operation of OLTCs, specific patterns and signatures can be extracted to identify underlying faults or abnormalities.

This paper presents a novel approach that combines voiceprint detection with MATLAB analysis to enhance fault monitoring in OLTC. The proposed method harnesses the unique acoustic emissions produced by OLTC during operation and utilizes MATLAB's powerful analysis capabilities to accurately detect and classify faults.

2. Tap Changer Condition Monitoring

Tap changers are essential components in power transformers that allow adjustment of the turns ratio and voltage levels. Corroborating the reliable operation of tap changers is crucial for maintaining a stable power supply. (Aziz *et al.* 2016) [2] focused in his research on online tap changer condition monitoring using vibration analysis. The authors developed a method to assess the condition of tap changers by analyzing the vibration signals generated during operation. Experimental results have demonstrated the effectiveness of the proposed technique in detecting abnormal conditions and incipient faults in tap changers. We can mention as well, (Li *et al.* 2019) [3] who presented a tap changer condition monitoring method using electrical measurements. The authors utilized online monitoring of contact resistance and current waveform analysis to identify abnormal operating conditions, such as contact wear or arcing. The approach demonstrated good sensitivity and reliability in detecting tap changer faults classification.

2.1. On-Load Tap-Changers (OLTC) Monitoring System

The system monitoring was built according to the knowledge of dominant failure modes and failure statistics of On-Load Tap-Changers (OLTC). This involves a transducer module a signal pre-amplification module, a data acquisition module, an isolation module, and a PC. The system demonstrated high accuracy in detecting arcing, contact resistance variations, and mechanical abnormalities of the OLTC. A conceptual model of tap changer fault detection procedure is shown in **Figure 1**.

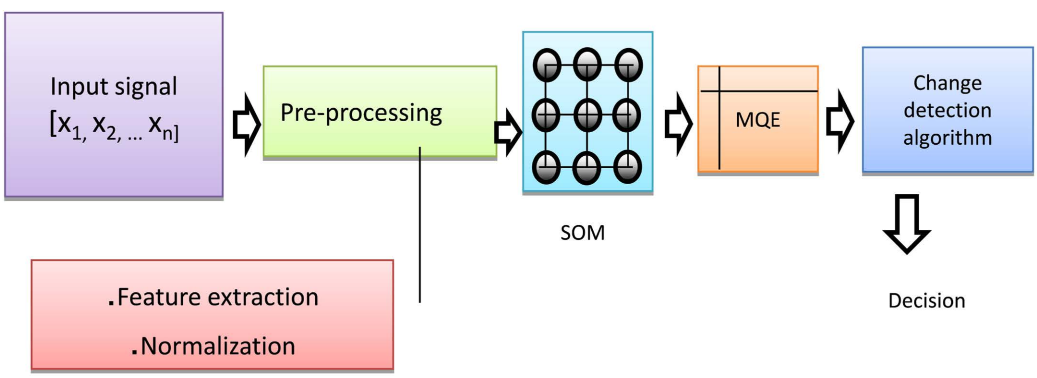

Figure 1. A conceptual model of tap changer fault detection.

Figure 1 illustrates a vibration signature measured using the monitoring system from a distribution type tap-changer. This specific vibration signature involves four particular vibration bursts. Each vibration is produced by a specific contact movement of the tap changer.

2.2. Voiceprint Detection Theory

Voiceprint recognition, also known as speaker verification or voice biometric, is a technology that involves identifying an individual based on their unique vocal characteristics (Ampbell, J. P. & Sturim, D. E. 2010) [4]. The basic theory behind voiceprint recognition revolves around the concept that each person has distinct vocal characteristics, including factors like pitch, tone, accent, and speech patterns (Reynolds, D. A. 2002) [5].

These characteristics shown in Figure 2, create a unique "voiceprint" for every individual, similar to a fingerprint. Voiceprint recognition works by capturing an individual's voice sample and extracting relevant features from it. These features capture the distinct vocal characteristics that can be used for identification and authentication purposes (Reynolds, D. A. & Rose, R. C. 1995) [6].

2.3. Voiceprint Detection and Its Applications in Fault Monitoring

One innovative approach for online fault monitoring of OLTCs definitely involves the use of voiceprint detection. Voiceprint is a technology that captures and analyzes the sound emissions produced by the tap-changer during operation. Therefore, it's crucial to note that abnormal sound patterns can indicate potential faults or anomalies in the OLTC, allowing proactive maintenance and reducing unplanned downtime (M. Jian and L. Yongmei, 2015) [7].

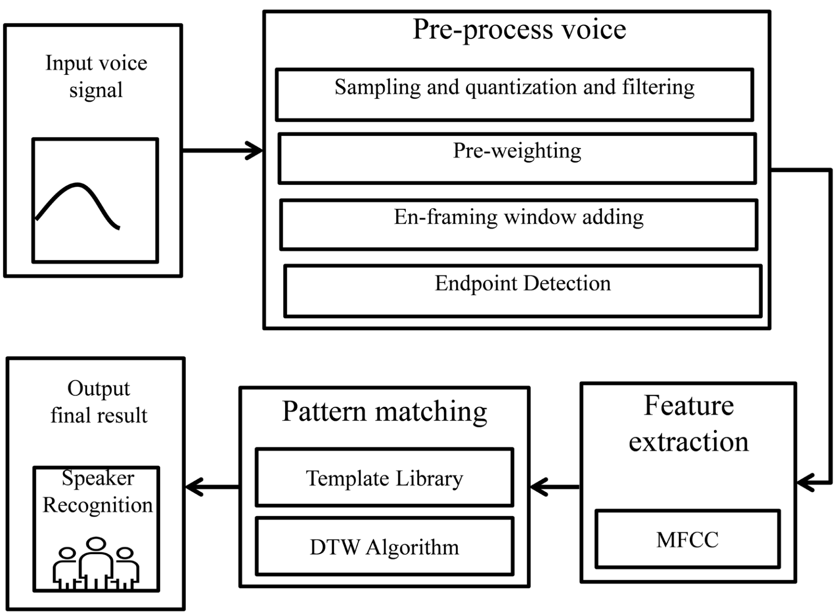

Figure 2. The theory of voiceprint recognition.

A research by (Wang *et al.* 2018) [8] examined the application of voiceprint detection for fault diagnosis of OLTCs. The study developed a voiceprint recognition system using Mel-frequency cepstral coefficients (MFCCs) and Gaussian mixture models (GMMs).

Experimental results demonstrated high accuracy in detecting tap-changer faults, including contacts misalignment and insulation deterioration.

In a similar vein, (Li *et al.* 2019) [9] proposed an optimized voiceprint detection method for fault monitoring and diagnosis of OLTCs. The authors utilized the Teager energy operator (TEO) to extract sensitive fault features from the sound signals. The approach achieved a robust fault detection capability, accurately identifying tap-changer faults such as flashback and welding.

2.4. Voiceprint Detection for Fault Classification

Voiceprint detection has also been explored for fault classification in OLTCs. (Zhang *et al.* 2020) [10] presented a fault classification model based on voiceprint features extracted using the wavelet packet transform (WPT) and linear discriminant analysis (LDA). The model achieved high accuracy in discriminating between normal operation and various fault types, such as contact erosion and winding disconnection. Furthermore, Xu *et al.* (2021) [11] proposed a convolutional neural network (CNN) model for automatic fault classification in OLTCs using voiceprint features. The model utilized a combination of time-domain and frequency-domain features extracted from the voiceprint signals. Experimental results demonstrated improved fault classification performance compared to traditional methods.

2.5. Voiceprint Time Spectrum

Mel Time Spectrum

Various new methods have emerged in the time field-frequency analysis field. Among them, we can count the empirical mode decomposition and wavelet that are often utilized (Paggi, M., Carrara, S. and Montagnari, F. 2018) [12]. The time frequency signal is obtained from Fourier transform is highly generated by time frequency spectrum data (Goo, E.C., Kim, Y.K. and Kim, C. 2020) [13]. This study uses the Mel filter to reduce of the time spectrum of the power transformer fault voice, print signal. The conversion relationship between the two scales is shown in **Equation 1**.

$$Mel(k) = 2595 \times \lg(1 + f/700)$$

It's clear that a voiceprint signal can easily be distinguished by people, mostly when it's in a low frequency. On the other hand, humans become insensitive when the frequency range is high. Therefore, in order to find the most compatible voiceprint feature for humans, the usual and common frequency scale is often converted into the Mel frequency scale to form a linear relationship between the human ear's perceptions. The transfer function of the filter bank is shown in **Equation 2.**

$$H_m(f)=\begin{cases}0,\ f<x(m-1)\\ \dfrac{f-x(m-1)}{x(m)-x(m-1)},x(m-1)\le f\le x(m)\\ \dfrac{x(m+1)-f}{x(m+1)-x(m)},x(m)\le f\le x(m+1)\\ 0,\ f>x(m+1)\end{cases}$$

Where "m" is the filter bank number, the number of filters in this paper is set to 30, and "x (m)" is the center frequency of the triangular filter, as shown in **Equation 3.**

$$x(m)=\left(\frac{C}{f_s}\right)Mel^{-1}\left(Mel(f_{\min})+m\frac{Mel(f_{\max})-Mel(f_{\min})}{M+1}\right)$$

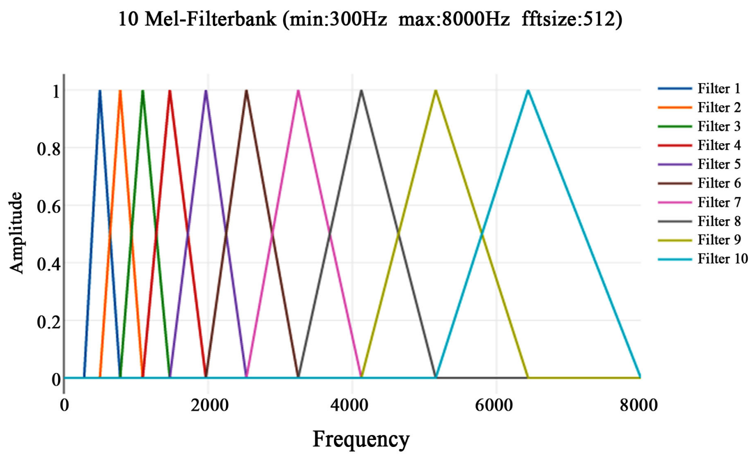

Figure 3. Mel filter blank.

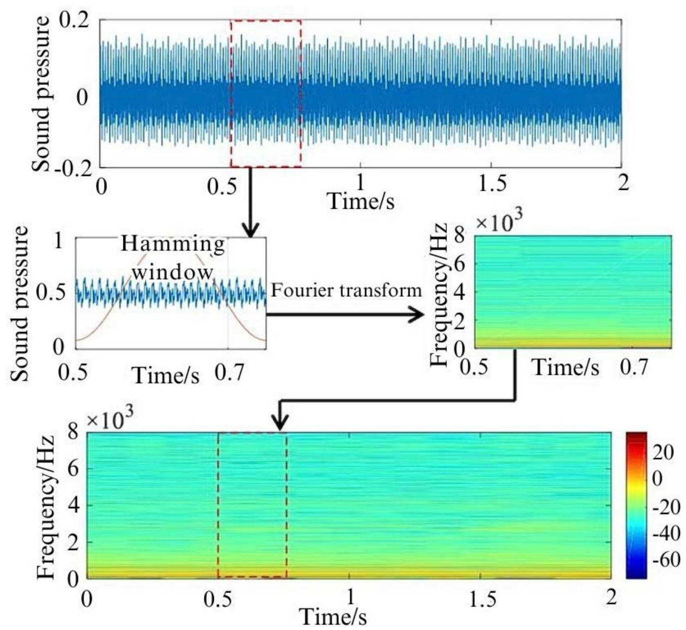

Figure 4. Drawing process of Mel time spectrum.

"Max" and "f min" are the maximum and minimum frequency values of the filtering Range. The sampling frequency of the acoustic sensor, which is taken as 16 kHz; "C" is the frame length of the discrete Fourier transform.

Figure 3 and Figure 4 illustrate Mel filter bank matrix which is multiplied order to obtain the voiceprint Mel-time frequency spectrum. The acquisition of the time spectrum of a voiceprint is done through MATLAB, relying on the following steps: The audio signal is loaded by using the audio read function to load the audio file containing the voice data. This is followed by the pre-processing techniques, such as filtering or normalization, which is done to enhance the voice signal. In this case, a band-pass filter was applied using the Band-passfuction. The Mel-time spectrum drawing process is illustrated on Figure 4.

3. Experimental Verification

3.1. Source of Experimental Data

To verify the voiceprint detection appropriate sensors were set up to acquire voice signals generated by the OLTC system, and a suitable recording device where used to capture the audio signals. The recorded voice signals were loaded into MATLAB, MATLAB which is a numerical computing environment and fourth-generation programming language which is developed by MathWorks. The voice signal was then used with preprocessing techniques such as filtering which were applied to remove noise and interference. MATLAB functions like "audioread" were used to load the audio signals, and signal processing functions like "bandpass" or "medfilt1" for filtering.

Frq2mel .m: Convert Hertz to Mel Scale;
Mel2frq .m: Convert Mel Scale to Hertz;
Rfft. m: FFT of Real Data;
rdct. m: DCT of Real Data;
Enframe. m: Divide a Voiceprint Signal into Frames;
Lpc. m: Convert Between Alternative LPC Representation;
Kmeans. m: Vector Quantisation, K-Means Algorithm;
Melbankm. m: Mel Filter bank Transformation Matrix;
Melcepst. m: Mel Cepstrum Frontend for Recognizer;
Gaussmix. m: Fit a Gaussian Mixture Model to Data Values.

3.2. Signal Processing Techniques

Fourier Transform technique was used to decompose a time-domain signal into its frequency components. By applying the FT, we have inspected the frequency content of the audio data captured from the OLTC system and analyze any changes or anomalies in the spectrum. MATLAB provided built-in functions such as fft and spectrogram to perform Fourier analysis. Spectral analysis techniques such as periodogram, power spectral density estimation, and spectrograms were employed to analyze the frequency content and changes in the OLTC audio data. MATLAB has functions like periodogram, pwelch, and spectrogram for spectral analysis.

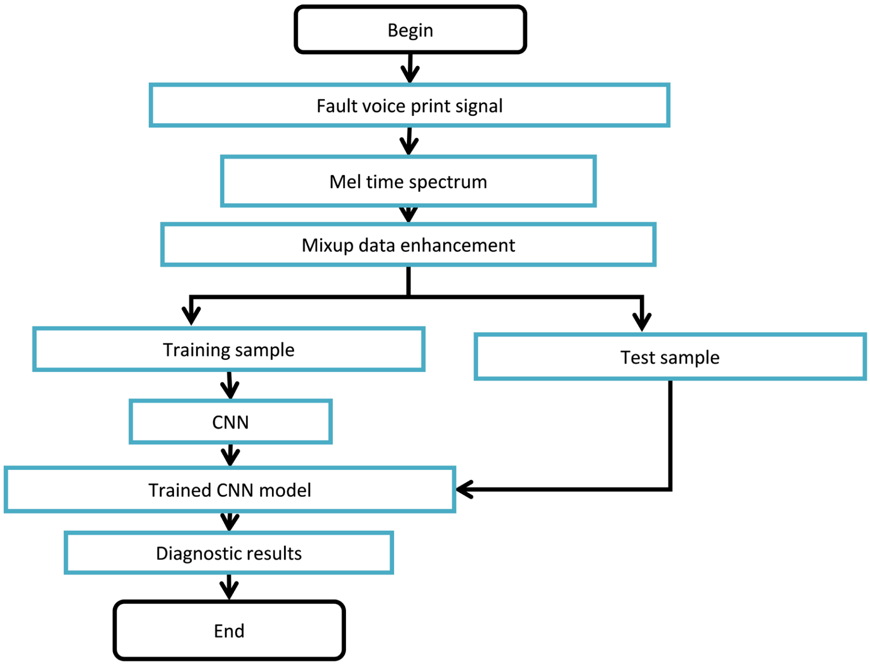

Figure 5. Voiceprint signal diagnostic process flow chart.

3.3. Flow Chart of the Experiment

In the context of online fault monitoring of On-Load Tap-Changer (OLTC) based on voiceprint detection, the voiceprint signal diagnosis process plays a crucial role in identifying and analyzing faults in the OLTC system. This section discusses the steps involved in the voiceprint signal diagnosis process. The first step of the diagnosis process is to acquire the voice signals generated by the OLTC system. The signal Diagnostic process flow chart is shown on the Figure 5.

This is done through appropriate sensors or microphones placed in the vicinity of the OLTC. The acquired signals are typically in the form of audio recordings. It provides a visual representation of the sequential procedures followed to extract information from voiceprints for various applications such as speaker identification, speaker verification, and forensic voice analysis. t: signal processing techniques.

Feature Extraction

Relevant features were extracted from the processed signal by using MATLAB functions such as spectrogram to calculate spectrogram. We have then used Matlab's signal processing toolbox MFCC for the extraction other features. We have Nx = 1024 samples of a signal that consists of a sum of sinusoids. The normalized frequencies of the sinusoids are $2\pi/5$ rad/sample and $4\pi/5$ rad/sample. The higher frequency sinusoid has 10 times the amplitude of the other sinusoid. The confusion matrix is utilized to represent the accuracy of the four datasets. The Mel mix-up analyses in the accurately classifies the voiceprint data of transformers in various states.

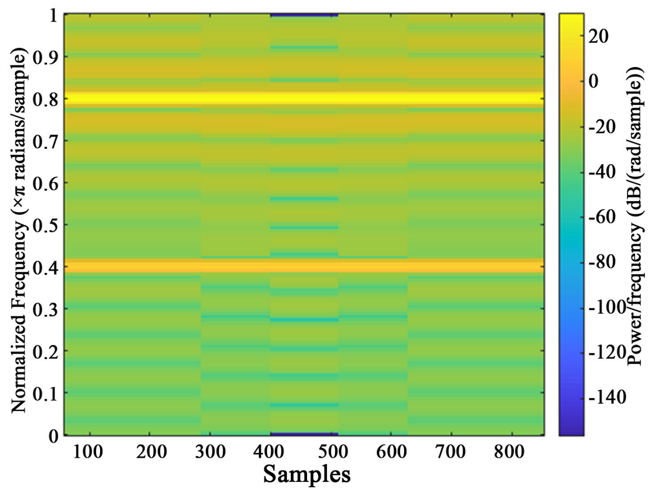

Figure 6. A time spectrogram graph of a vibration signal.

In **Figure 6**, we have Nx =1024 samples of a signal that consists of a sum of sinusoids. The normalized frequencies of the sinusoids are 2π/5 rad/sample and 4π/5 rad/sample. The higher frequency sinusoid has 10 times the amplitude of the other sinusoid.

3.4. Classification Algorithm

Once the features are extracted and represented, a classification algorithm is applied to classify the voice signals into different fault categories. The confusion matrix is the most intuitive and simple method to measure the accuracy of the classification. The classification algorithm is trained on a labeled dataset consisting of voice signals with known fault conditions to learn the patterns and characteristics associated with each fault type (Ali, M.A., Babar, M.M., Afaq, F. and Malik, N.H. 2021) [14]. Fault Identification and Analysis: After classification, the diagnosed fault type is identified based on the classification results.

Each fault type corresponds to a specific fault condition in the OLTC system. The analysis of the diagnosed faults involves studying the patterns and characteristics associated with each fault to understand their impact on the OLTC's performance and functionality. This analysis can aid in maintenance decision-making and preventive measures to ensure the reliable operation of the OLTC system. It is important to note that the effectiveness of the voiceprint signal diagnosis process depends on the quality of the acquired signals, appropriate preprocessing techniques, relevant feature extraction methods, and accurate classification algorithms. Continuous refinement and optimization of these steps can lead to improved fault detection and monitoring of the OLTC system Represent the extracted features in a suitable format for further analysis. Create a feature matrix or vector using MATLAB's matrix operations. You may also consider applying dimensionality reduction techniques like PCA using functions such as "pca" or "pcares" to reduce the dimensionality of the feature space. This is illustrated in **Figure 7**.

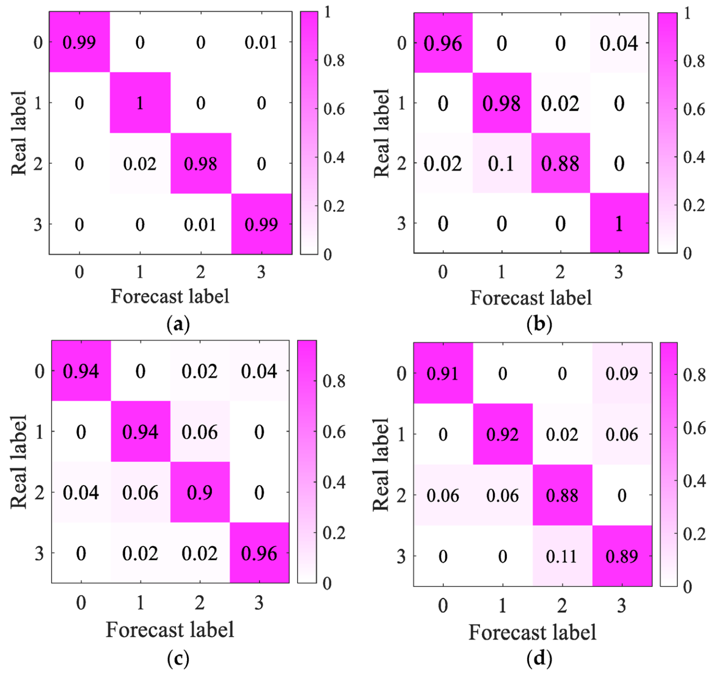

Figure 7. Fault classification confusion matrix.

3.5. Fault Detection

The trained classification model IS applied to new, unseen voice signals to diagnose faults. The fault types are determined by comparing the predicted outputs with the known fault categories. The analysis of the diagnosed faults is based on the characteristics associated with each fault type. The raw audio signals from the OLTC monitoring system were loaded into MATLAB, followed by, resampling, filtering, and normalization, to prepare the data for analysis. Relevant features were extracted from the preprocessed audio data that were used for voiceprint detection. One of these features includes Mel Frequency Cepstral Coefficients (MFCCs).

3.6. Mel Frequency Cepstral Coefficients (MFCCs) and the Acoustic Signals Emittion

Mel Frequency Cepstral Coefficients (MFCCs) are a feature extraction method widely used in speech and audio signal processing. MFCCs are designed to capture the essential characteristics of a speech signal by representing the spectral content of the signal in a compact and discriminative form. Cepstral upgrade window: after each data frame was calculated and got a result of the K-order MFCC parameters, the K coefficients are multiplied by different weights, it is actually a short window, such as formula shown in **Equation 4**:

$$C_k = \sum_{j=1}^{24} \log\left(P_j\right) \cos\left[k\left(j-\frac{1}{2}\right)\frac{\pi}{24}\right]$$

$$W_k = 1 + \frac{K}{2}\sin\left(\frac{\pi k}{K}\right)$$

Check the points of cepstral parameters: If standard MFCC parameters could reflected the static characteristic of the voice parameter, the human ear is more sensitive to the dynamic characteristics of speech (W. Lin, L. Yang, and B. Xu, 2006) [15]. Differential inverted dive parameters are used to describing the dynamic characteristics, as shown in **Equation 5.**

$$\Delta C(n) = \frac{1}{\sqrt{\sum_{i=-k}^{k} i^2}} \sum_{i=-k}^{k} i \cdot C(n+i), 1 \le n \le k$$

During normal operation, OLTC produced minimal acoustic signals. However, when faults occur, contact wear, loose connections, or arcing, the acoustic emissions changed. These changes in the acoustic signals were indicative of the specific fault type and severity. Voiceprint detection using MATLAB involves capturing and analyzing the acoustic signals emitted by the OLTC during fault conditions. These signals were typically captured using microphones or acoustic sensors placed in close proximity to the OLTC. The signals were then processed and analyzed using MATLAB algorithms to extract features that are characteristic of various fault conditions.

4. System Simulation

GUI MATLAB was then used to achieve the operating interface of the system. The user interface about the recognition system of the speaker and isolated words, the accuracy rate of test system is as shown in follows in **Table 1**.

On **Table 1**, six testers had ten groups of independent experiments. In each groups of test, six testers inputted indifferent isolate word or template library that was founded in voice signal based on speech text, and respectively inputted same voice signal to conduct this simulation.

5. Limitation and Challenges

The acquisition and processing data for voiceprint detection can be challenging. Collecting high-quality voice samples in real-time from the OLTC was a complex task. Factors such as background noise, varying operational conditions, and hardware limitation have affected the quality of acquired data. Developing accurate and robust algorithms for voiceprint detection using MATLAB was a challenging task. Voiceprints are intricate, therefore can be affected by factors like pitch, accent, and speech variations. Proper feature extraction and selection techniques were need to be employed to ensure reliable fault detection. The presence of background noise or interference has affected the accuracy of fault detection using voiceprint analysis.

Table 1. Accuracy rate of speaker recognition system.

Group number	1	2	3	4	5
Recognition rate	100%	100%	100%	100%	100%
Group number	6	7	8	9	10
Recognition rate	100%	100%	100%	100%	100%

However, there are several advantages of using voiceprint detection for online fault monitoring of OLTC. Sensor reliability is one of those. In fact Voiceprint detection utilizes microphones or acoustic sensors, which are generally reliable and widely available. They can capture the acoustic signals emitted by the OLTC for analysis. Real-time implementation, with advancements in signal processing and computational capabilities, voiceprint detection can be implemented in real-time, providing instant feedback on the OLTC's condition.

6. Conclusion

Voiceprint detection has emerged as a promising technique for online fault monitoring and diagnosis of on-load tap-changers. Studies by (Wang *et al.* 2018) [8], (Li *et al.* 2019) [9], (Zhang *et al.* 2020), and (Xu *et al.* 2021) [11] demonstrate the effectiveness of voiceprint analysis in detecting and classifying various faults in OLTCs. These findings offer valuable insights for developing practical and reliable fault monitoring systems in power systems, facilitating proactive maintenance and enhancing overall system reliability. In this experiment MATLAB has been a viable approach for online fault monitoring of On-Load Tap Changers (OLTC). It offered several advantages, including sensor reliability, non-contact monitoring, fault identification, and real-time implementation. By capturing unique acoustic patterns associated with faults, voiceprint detection can aid in timely maintenance and repairs.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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