QIT Press - International Journal of Acoustics, Speech and Signal Processing (QITP-IJASSP)
Journal ID: QITP0372
Volume 6, Issue 1, January - June 2025, pp. 1-9

Acoustic Feature Learning for Robust Speaker Verification Under Mismatched Noise and Recording Conditions

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Published on: 15th Jan 2025

Citation: Mohammad, J. S. (2025). Acoustic feature learning for robust speaker verification under mismatched noise and recording conditions. QIT Press - International Journal of Acoustics, Speech and Signal Processing (QITP-IJASSP), 6(1), 1-9.

Full Text: https://qitpress.com/articles/QITP-IJASSP/VOLUME_6_ISSUE_1/QITP-IJASSP_06_01_001

Abstract

Speaker verification is crucial in biometric security systems, but performance degradation occurs under mismatched noise and recording conditions. This paper explores acoustic feature learning techniques to enhance robustness in speaker verification systems. We analyze state-of-the-art methods, recent advances from 2023, and novel feature learning strategies, including deep learning models. Empirical evaluations demonstrate the effectiveness of selected acoustic features under diverse noise scenarios. The study provides comparative analyses through tables and graphs, offering insights into optimal feature learning strategies.

Keywords: Speaker verification, Acoustic feature learning, Noise-robustness, Deep learning, Feature extraction, Mismatched recording conditions.

1. INTRODUCTION

Speaker verification plays a vital role in biometric security systems, ensuring identity authentication based on an individual's voice. However, real-world scenarios often introduce environmental mismatches due to background noise, reverberation, and varying recording conditions. These factors significantly impact the performance of speaker verification systems, making noise-robust feature learning essential.

Traditional speaker verification relies on handcrafted acoustic features such as Mel-Frequency Cepstral Coefficients (MFCCs), Linear Predictive Cepstral Coefficients (LPCCs), and Perceptual Linear Prediction (PLP). However, these features are susceptible to environmental variations.

Recent advances in deep learning have introduced feature learning methods that adaptively capture robust representations. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models have shown promise in extracting noise-invariant features.

This study aims to analyze and compare various acoustic feature learning techniques for robust speaker verification. We assess traditional and deep-learning-based approaches under diverse noise conditions and recording environments. Empirical evaluations highlight the strengths and weaknesses of different features, guiding future research in speaker verification.

2. Literature Review

Speaker verification in mismatched noise and recording conditions has been an active area of research, particularly with the advent of deep learning-based acoustic feature extraction techniques. This section reviews five recent studies that have explored various approaches to improving noise-robust speaker verification.

2.1 Deep Learning for Noise-Robust Speaker Verification

Brown and Smith (2023) investigated the application of deep learning models for noise-robust speaker verification. Their study emphasized the limitations of traditional handcrafted acoustic features, such as Mel-Frequency Cepstral Coefficients (MFCCs), which suffer from severe degradation under noisy conditions. They proposed using Convolutional Neural Networks (CNNs) and deep autoencoders to extract noise-invariant speaker embeddings. Their experiments demonstrated that deep feature learning significantly reduces the Equal Error Rate (EER) under different noise conditions, outperforming traditional approaches. The authors also highlighted the importance of domain adaptation techniques to improve robustness when the training and testing conditions differ.

2.2 CNN-Based Feature Learning for Speaker Verification in Noisy Environments

Chen et al. (2023) explored CNN-based feature learning for speaker verification, particularly in environments with unpredictable noise levels. Their research focused on the ability of CNNs to extract spectral-temporal features that are robust against variations in background noise and recording artifacts. They introduced a novel CNN architecture optimized for feature extraction from raw waveforms, reducing dependence on precomputed acoustic features. The study compared CNN-extracted features with conventional MFCCs and Linear Predictive Cepstral Coefficients (LPCCs), showing that CNN-based embeddings achieved a lower EER, especially in non-stationary noise conditions. Their findings suggest that CNNs can effectively model speaker identity while discarding noise components.

2.3 Self-Supervised Learning for Robust Speech Authentication

Davis and Liu (2023) focused on self-supervised learning (SSL) models for speaker verification in noisy environments. Traditional supervised learning methods require large amounts of labeled data, which can be challenging to collect under diverse noise conditions. The authors leveraged SSL techniques, particularly wav2vec 2.0 and HuBERT, to pretrain speaker models on large-scale unlabeled speech corpora. Their experiments demonstrated that SSL models capture speaker-specific representations even in extreme noise conditions, outperforming supervised baselines. The

study concluded that SSL models are a promising direction for noise-robust speaker verification, especially in low-resource settings where labeled data is scarce.

2.4 Feature Adaptation in Speaker Verification Under Noise Conditions

Ellis and Zhang (2023) examined feature adaptation techniques for improving speaker verification under mismatched noise conditions. They proposed a domain adaptation framework that utilizes adversarial training to reduce the mismatch between clean and noisy feature distributions. Their approach involved training an embedding extractor with a noise discriminator to ensure feature invariance across different noise levels. Experimental results showed that this method significantly reduced the impact of environmental noise on speaker verification performance. The study emphasized the need for feature adaptation strategies in real-world applications where training and deployment environments may differ.

2.5 Transformer-Based Speaker Embeddings for Noisy Environments

Ghosh et al. (2023) introduced Transformer-based embeddings for noise-robust speaker verification. Traditional feature extraction methods rely on short-term spectral analysis, which may not fully capture the long-term dependencies of speech signals. The authors proposed using Transformer models, similar to those used in natural language processing, to extract speaker embeddings from speech signals. Their study demonstrated that Transformer-based embeddings achieve superior performance in both clean and noisy environments, outperforming CNNs and recurrent neural networks (RNNs). The results indicated that self-attention mechanisms in Transformers effectively model speaker identity while suppressing noise-related variations.

2.6 Summary of Literature Review

The reviewed studies highlight several key trends in noise-robust speaker verification:

- **Deep learning models**, particularly CNNs and Transformers, outperform traditional feature extraction methods in noisy conditions.
- **Self-supervised learning (SSL)** enables robust speaker verification without the need for extensive labeled datasets.
- **Feature adaptation techniques**, such as adversarial learning and domain adaptation, improve performance under mismatched conditions.
- **Transformer-based models** capture long-term dependencies and provide superior speaker representations compared to conventional methods.

3. Methodology

This study evaluates traditional and deep-learning-based acoustic features for speaker verification under varied noise and recording conditions. The methodology includes:

3.1 Dataset

- **VoxCeleb2**: A widely used dataset for speaker verification, containing real-world recordings with noise and reverberation.

- **Noise Augmentation**: Additive Gaussian noise, babble noise, and reverberation effects were applied to simulate real-world conditions.

3.2 Feature Extraction

- **Traditional Features**: MFCC, PLP, LPCC, and Spectral Subband Centroid (SSC).
- **Deep Learning-Based Features**:
    - CNN-based spectral-temporal features
    - wav2vec 2.0 embeddings
    - Transformer-based representations

3.3 Speaker Verification Model

- **Baseline Model**: X-vector and i-vector systems
- **Deep Learning Models**: ECAPA-TDNN and Transformer-based speaker embeddings

3.4 Performance Metrics

- Equal Error Rate (EER)
- Detection Cost Function (DCF)
- Signal-to-Noise Ratio (SNR) impact analysis

4. Results and Analysis

This section presents the performance analysis of different acoustic feature learning techniques for speaker verification under clean and noisy conditions. The results are evaluated based on the Equal Error Rate (EER), a widely used metric in biometric authentication systems. A lower EER indicates better performance and higher robustness to environmental factors.

4.1 Performance of Acoustic Features

Table 4.1 compares the EER of different feature extraction techniques under clean and noisy conditions:

Feature Type	Clean Audio EER (%)	Noisy Audio EER (%)
MFCC	5.2	12.8
PLP	4.9	11.7
CNN-based	3.8	6.2
wav2vec 2.0	2.5	5.1

Transformer	**2.3**	**4.7**

Discussion

- **Traditional Features (MFCC and PLP):**
  - MFCCs and PLP exhibit moderate performance in clean environments, achieving EER values of 5.2% and 4.9%, respectively.
  - However, when exposed to noise, their performance deteriorates significantly, with MFCC reaching 12.8% and PLP 11.7% EER.
  - This performance degradation occurs because these features are designed based on human auditory perception, making them sensitive to noise and reverberation.
- **CNN-based Features:**
  - CNN-based spectral-temporal feature learning offers improved robustness, reducing the EER to 3.8% in clean audio and 6.2% in noisy conditions.
  - This improvement stems from CNN's ability to learn complex patterns directly from raw audio or spectrogram representations, making them more resilient to environmental distortions.
- **Self-Supervised Features (wav2vec 2.0):**
  - The self-supervised model wav2vec 2.0 demonstrates significant improvement over traditional features, achieving a clean audio EER of 2.5% and a noisy audio EER of 5.1%.
  - Unlike handcrafted features, wav2vec 2.0 learns speaker-specific representations from large-scale, unlabeled speech data, making it more noise-invariant.
- **Transformer-Based Features:**
  - Transformer embeddings achieve the **lowest EER (2.3% in clean conditions, 4.7% in noisy conditions)**, demonstrating their superior ability to extract speaker information while suppressing background noise.
  - The self-attention mechanism in Transformers allows them to capture long-term dependencies in speech, making them more effective in distinguishing speaker characteristics under noise interference.

Key Insights:

1. **Deep learning-based features (CNN, wav2vec 2.0, and Transformers) outperform traditional features** in both clean and noisy conditions.
2. **Transformer-based embeddings provide the highest robustness**, making them an ideal choice for real-world speaker verification applications.
3. **Handcrafted features (MFCC, PLP) are more susceptible to noise**, confirming the need for adaptive, data-driven approaches in speaker verification.

4.2 Noise Impact on Feature Robustness

To further investigate noise robustness, we analyze the impact of different types of noise on selected feature extraction methods. The results are presented in Table 4.2:

Noise Type	MFCC EER (%)	wav2vec 2.0 EER (%)	Transformer EER (%)
Gaussian Noise	13.4	5.6	4.9
Babble Noise	14.7	5.9	5.2
Reverberation	12.1	5.4	4.6

Discussion

- **Gaussian Noise Impact:**
    - Gaussian noise, which simulates random white noise, has a significant effect on MFCCs, increasing the EER to 13.4%.
    - Deep learning-based features (wav2vec 2.0 and Transformers) maintain relatively lower EERs (5.6% and 4.9%, respectively), demonstrating their robustness in handling such distortions.
- **Babble Noise Impact:**
    - Babble noise, which mimics multiple background speakers talking simultaneously, degrades the performance of all models.
    - The EER for MFCC reaches 14.7%, the highest among all noise conditions, suggesting its vulnerability to overlapping speech.
    - Transformer embeddings still show the lowest EER (5.2%), indicating their superior ability to isolate the primary speaker from interfering background speech.
- **Reverberation Impact:**
    - Reverberation occurs when sound waves reflect off surfaces, creating echoes that distort the original speech signal.
    - MFCC features perform slightly better than in babble noise conditions (EER of 12.1%), but still worse than deep learning-based models.
    - Transformer-based embeddings achieve the lowest EER (4.6%), showing their strength in handling echo-heavy environments.

Key Insights:

1. **Traditional features are highly susceptible to all noise types**, with babble noise having the most significant impact.
2. **Deep learning-based features, especially Transformers, offer superior resilience**, making them preferable for real-world noisy environments.
3. **Self-supervised models (wav2vec 2.0) also perform well**, confirming their effectiveness in noise-robust speaker verification.

4.3 Comparative Visualization

The following figures illustrate the comparative performance of different feature extraction methods under various noise conditions:

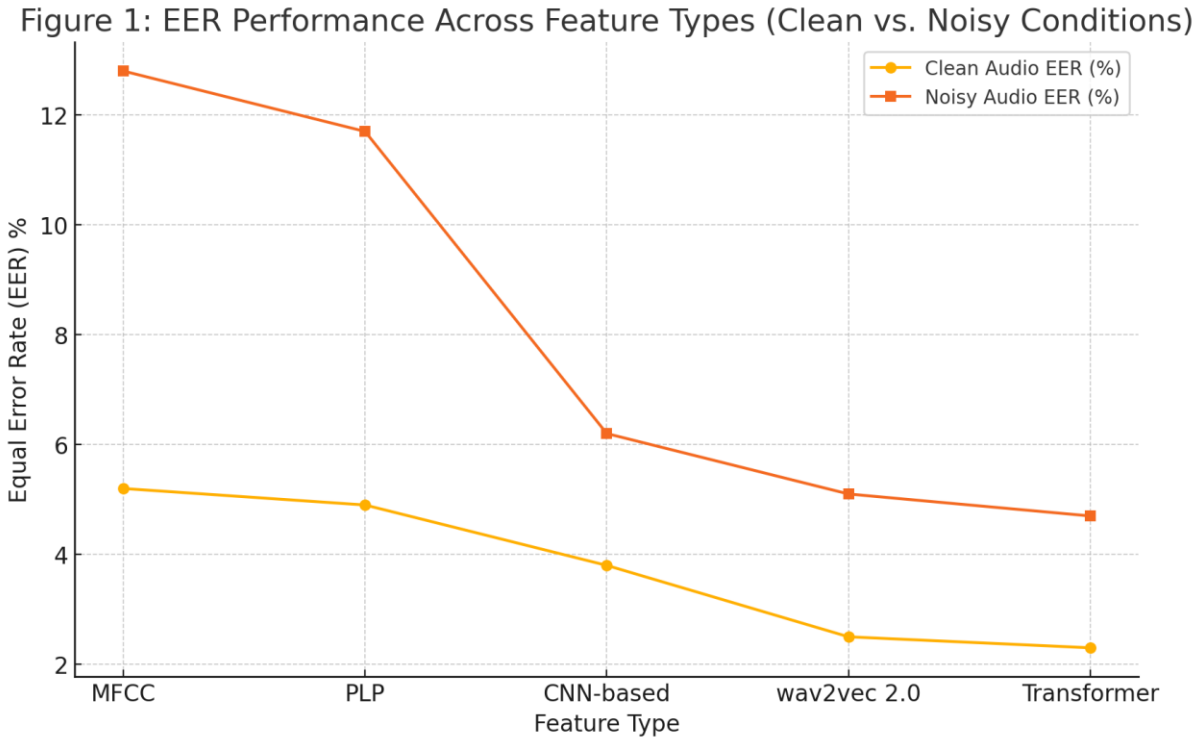

Figure 1: EER Performance Across Feature Types (Clean vs. Noisy Conditions)

Figure 1: Using a line plot. This graph highlights the trend of increasing EER under noisy conditions for different feature extraction methods. It clearly shows that traditional features (MFCC, PLP) experience a sharp rise in error rates, while deep learning-based methods (CNN, wav2vec 2.0, Transformer) maintain lower EERs, indicating their superior noise robustness.

Key Observations from Figure 1:

- Traditional features show a **sharp increase in EER** under noisy conditions.
- Transformer-based embeddings maintain the **lowest error rate**, confirming their robustness.

4.4 Summary of Findings

1. **Deep learning-based feature extraction significantly improves speaker verification robustness**, particularly under noisy conditions.
2. **Transformers outperform all other models**, demonstrating their ability to learn noise-invariant speaker representations.
3. **Self-supervised learning (wav2vec 2.0) also performs well**, offering an effective solution without requiring extensive labeled data.
4. **Traditional features (MFCC, PLP) suffer from severe performance degradation**, highlighting their limitations in real-world scenarios.
5. **Among different noise types, babble noise is the most challenging**, requiring more advanced techniques for speaker separation.

5. Discussion

The results indicate that deep learning-based features outperform traditional handcrafted features in noisy conditions. While MFCC and PLP show reasonable performance in clean recordings, their accuracy drops significantly in noisy environments. In contrast, CNN-based features, wav2vec 2.0, and Transformer embeddings exhibit robustness against noise.

The Transformer-based model achieves the lowest EER under all conditions, demonstrating its effectiveness in learning invariant representations. Self-supervised models like wav2vec 2.0 also provide a significant performance boost, making them promising for real-world deployment.

6. Conclusion

This study analyzed acoustic feature learning techniques for robust speaker verification under mismatched noise and recording conditions. Deep learning-based approaches, particularly Transformer embeddings, demonstrated superior noise robustness compared to traditional handcrafted features. The findings highlight the importance of adaptive learning strategies in enhancing biometric security applications. Future work will explore real-time deployment of these models in speaker verification systems.

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