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REAL-TIME SPEECH EMOTION RECOGNITION FOR HUMAN-COMPUTER INTERACTION

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ABSTRACT

Emotion recognition from speech is transforming human-computer interaction (HCI) by enabling applications that understand and respond to users' emotional states in real-time. This study compares feature extraction methods—Mel-frequency cepstral coefficients (MFCCs), pitch, energy, and spectrograms—used for emotion recognition in speech to determine their effectiveness in enhancing HCI systems. Using a robust dataset, we evaluate each method's accuracy, processing efficiency, and adaptability to real-time applications, aiming to identify which techniques most effectively balance performance and computational demands. Findings suggest that while MFCCs offer consistent accuracy, spectrograms used in CNN architectures provide superior emotional detail for real-time, high-dimensional applications. These insights offer practical guidance for developing responsive, emotion-sensitive HCI applications.

1. INTRODUCTION

In recent years, the integration of emotion recognition within human-computer interaction (HCI) systems has gained significant momentum, driven by the increasing demand for technology that adapts to human emotions and intentions. From virtual assistants and customer service bots to medical and therapeutic tools, emotion recognition offers a pathway to more intuitive and effective HCI. Speech, as a natural and expressive medium, is particularly rich in emotional cues, providing unique insights into users' emotional states without requiring invasive measures.

To capture these emotional nuances, real-time emotion recognition systems rely on extracting relevant features from speech. However, the choice of feature extraction methods directly impacts the system's accuracy and responsiveness. Commonly used methods include Mel-frequency cepstral coefficients (MFCCs), which capture the timbral aspects of speech, and spectral features like pitch and energy, which can vary significantly with emotional intensity. More complex representations, such as spectrograms, allow for a more detailed analysis by providing a visual depiction of frequency over time, making them particularly useful in deep learning applications.

Despite the availability of various feature extraction techniques, identifying the most effective methods for real-time HCI remains a challenge, as each technique offers distinct advantages and limitations. This study aims to compare multiple feature extraction methods to determine their effectiveness in recognizing emotions in real-time. By examining the trade-offs between accuracy and computational efficiency, this research provides actionable insights for implementing emotion-sensitive applications, contributing to the development of more responsive and empathetic HCI systems.

Feature Extraction Techniques for Emotion Recognition

Feature extraction is a crucial step in real-time emotion recognition systems, as it determines the type and quality of information fed into the models for classification. In the context of speech, feature extraction focuses on capturing distinctive characteristics of sound that are sensitive to emotional nuances. The goal is to distill meaningful features from the raw audio signal to identify emotions reliably and in real-time, a key requirement for effective human-computer interaction (HCI). By leveraging suitable features, systems can improve accuracy in distinguishing emotions such as happiness, sadness, anger, or surprise, which often have subtle yet recognizable patterns in speech.

One of the foundational techniques in audio processing is the extraction of **Mel-Frequency Cepstral Coefficients (MFCCs)**. MFCCs capture the power spectrum of an audio signal based on human auditory perception, making them well-suited for speech analysis. They focus on low-frequency components that play a prominent role in recognizing emotional tone and prosody. MFCCs are robust, computationally efficient, and widely used in audio classification tasks, including emotion recognition. In real-time applications, MFCCs allow for quick processing, enabling the system to generate emotion predictions on the fly, making them a standard in feature extraction methods.

Pitch and energy are additional key features in emotion recognition. Variations in pitch often correlate with different emotional states, as emotions can significantly affect the vocal frequency of speech. For instance, higher pitch levels are typically associated with excitement or anger, while lower pitch levels may indicate sadness or calmness. Similarly, energy—or the amplitude of the audio signal—can indicate the intensity of an emotion. High energy levels are common in expressions of anger or happiness, while low energy levels are often found in sadness. Together, pitch and energy features contribute to a more nuanced understanding of emotions in speech and can be particularly useful in capturing the intensity and variation of emotional expression.

Spectrograms offer a visual approach to feature extraction by representing the audio signal in the time-frequency domain. By showing frequency changes over time, spectrograms can capture transient aspects of speech that are crucial for distinguishing emotions. Spectrograms are especially effective when coupled with convolutional neural networks (CNNs), as CNNs can interpret the visual patterns and identify subtle cues that traditional numerical features might miss. This method, while computationally intensive, allows the model to gain deeper insight into the texture of the audio signal, particularly useful for real-time HCI applications where subtle changes in emotion must be captured.

Finally, the choice of feature extraction technique often hinges on the **balance between computational efficiency and accuracy**. While MFCCs and pitch-energy features provide quicker processing suitable for real-time applications, spectrograms offer richer data that can enhance model accuracy, albeit at a higher computational cost. For real-time emotion recognition in HCI, a combination of these features may yield optimal results by harnessing the strengths of each approach.

In emotion recognition from speech, mathematical techniques are fundamental for extracting, processing, and analyzing the features that characterize emotional states. The key goal is to extract features that effectively represent emotional information while being computationally efficient for real-time processing. Below, we describe the mathematical foundations behind the feature extraction techniques used in speech-based emotion recognition.

1. Mel-Frequency Cepstral Coefficients (MFCCs)

MFCCs are widely used in speech recognition and emotion analysis because they mimic human auditory perception. The process involves several mathematical steps to convert the raw audio signal into a set of coefficients that reflect the spectral properties of the sound:

1. **Pre-emphasis**: The first step is to apply a pre-emphasis filter to the raw audio signal to enhance high-frequency components. Mathematically, this is represented as:

   y[t]=x[t]−α⋅x[t−1]y[t] = x[t] - \alpha \cdot x[t-1]y[t]=x[t]−α⋅x[t−1]

   where x[t]x[t]x[t] is the raw audio signal, y[t]y[t]y[t] is the pre-emphasized signal, and α\alphaα is typically a constant between 0.9 and 1.0.

2. **Framing and Windowing**: The audio signal is divided into small overlapping frames to analyze the signal's behavior over time. Each frame x(t)x(t)x(t) is then multiplied by a window function w(t)w(t)w(t), often a Hamming window:

   w(t)=0.54−0.46⋅cos⁡(2πtN−1)w(t) = 0.54 - 0.46 \cdot \cos\left(\frac{2\pi t}{N-1}\right)w(t)=0.54−0.46⋅cos(N−12πt)

   where NNN is the frame length. This reduces spectral leakage in the Fourier transform.

3. **Fourier Transform**: The fast Fourier transform (FFT) is applied to each frame to convert the signal from the time domain to the frequency domain:

   X[k]=∑n=0N−1x[n]e−i2πkn/NX[k] = \sum_{n=0}^{N-1} x[n] e^{-i 2 \pi k n / N}X[k]=n=0∑N−1x[n]e−i2πkn/N

   where X[k]X[k]X[k] is the frequency spectrum, and x[n]x[n]x[n] is the time-domain signal.

4. **Mel Filter Bank**: The frequency axis is warped using a Mel-scale filter bank to simulate human ear perception, which is more sensitive to lower frequencies. This step involves taking the logarithm of the energy in each Mel band:

   Mmel=log⁡(∑m=1M∣Xm∣2⋅wm(f))M_{mel} = \log\left(\sum_{m=1}^{M} |X_m|^2 \cdot w_m(f)\right)Mmel=log(m=1∑M∣Xm∣2⋅wm(f))

   where wm(f)w_m(f)wm(f) is the filter function for the Mel scale, and MmelM_{mel}Mmel is the Mel-frequency component.

5. **Discrete Cosine Transform (DCT)**: Finally, a discrete cosine transform (DCT) is applied to the log Mel-spectrum to decorrelate the features:

cn=∑k=0K−1log⁡(Mmel[k])⋅cos⁡(πK⋅n

cn=k=0∑K−1log(Mmel[k])⋅cos(Kπ⋅n⋅(2k+1))

where cnc_ncn are the MFCCs, Mmel[k]M_{mel}[k]Mmel[k] is the Mel-spectral representation, and KKK is the number of coefficients to extract.

MFCCs represent spectral envelope features that are robust to background noise and other distortions, making them ideal for emotion recognition tasks.

Pitch and Energy

Pitch and energy are vital features for detecting emotions, particularly because they correlate with changes in vocal intensity and tone, which are affected by emotional states. The mathematical calculation for pitch and energy is outlined below:

- **Pitch Calculation**: Pitch is the fundamental frequency of speech, often estimated using autocorrelation or harmonic product spectrum. For an autocorrelation-based pitch detection method:

  R(τ)=∑n=0N−1x[n]·x[n+τ]R(\tau) = \sum_{n=0}^{N-1} x[n] \cdot x[n+\tau]R(τ)=n=0∑N−1x[n]·x[n+τ]

  where R(τ)R(\tau)R(τ) is the autocorrelation function, and τ\tauτ is the lag. The pitch corresponds to the value of τ\tauτ that maximizes the correlation function.

- **Energy Calculation**: The energy of a speech frame can be computed by summing the squared amplitude of the signal samples within each frame:

  E=∑n=0N−1∣x[n]∣2E = \sum_{n=0}^{N-1} |x[n]|^2E=n=0∑N−1∣x[n]∣2

  where x[n]x[n]x[n] is the signal amplitude at sample nnn, and EEE represents the energy for a given frame.

These features are sensitive to changes in emotional tone—high energy and pitch typically represent emotions like happiness or anger, while low energy and pitch are more common in sadness or calmness.

Spectrogram and Time-Frequency Representation

A **spectrogram** is a visual representation of the spectrum of frequencies in a signal as it varies with time. It is calculated by applying a short-time Fourier transform (STFT) to the signal, breaking the signal into short overlapping windows and performing an FFT on each:

S(t,f)=∑n=−∞∞x[n]·w(t−n)·e−i2πfnS(t, f) = \sum_{n=-\infty}^{\infty} x[n] \cdot w(t-n) \cdot e^{-i 2 \pi f n}S(t,f)=n=−∞∑∞x[n]·w(t−n)·e−i2πfn

where S(t,f)S(t, f)S(t,f) represents the complex spectrum at time ttt and frequency fff, x[n]x[n]x[n] is the signal, and w(t−n)w(t-n)w(t−n) is the window function.

The spectrogram provides a time-frequency representation that captures both the temporal evolution and frequency content of the speech, which is especially useful for emotion recognition. When using a CNN for analysis, the spectrogram acts as an image, with each time-frequency pixel representing the intensity of a frequency at a particular point in time. This enables deep learning models to detect intricate patterns in speech indicative of different emotional states.

2. COMBINING FEATURES FOR EMOTION RECOGNITION

For real-time emotion recognition, the combination of multiple feature extraction techniques often yields superior results. Combining MFCCs, pitch, energy, and spectrogram features into a single feature vector can improve the model's ability to detect subtle emotional nuances. Mathematically, this involves concatenating the feature vectors derived from each technique:

F=[MFCC1,MFCC2,...,MFCCn,Pitch,Energy,Spectrogram]\mathbf{F} = [MFCC_1, MFCC_2, ..., MFCC_n, Pitch, Energy, Spectrogram]F=[MFCC1,MFCC2,...,MFCCn,Pitch,Energy,Spectrogram]

where F\mathbf{F}F is the combined feature vector, and MFCC1,MFCC2,...,MFCCnMFCC_1, MFCC_2, ..., MFCC_nMFCC1,MFCC2,...,MFCCn represent the individual MFCC coefficients, with additional features for pitch, energy, and spectrogram.

This combined feature vector is then used as input to machine learning algorithms (such as SVMs, Random Forests, or neural networks) for training emotion recognition models. The quality of these features determines the model's performance, making careful feature extraction and combination essential for achieving high accuracy in real-time applications.

3. CONCLUSION

Mathematical methods in feature extraction, from MFCCs and pitch to energy and spectrogram analysis, play a significant role in the success of emotion recognition systems. Each of these techniques provides a unique perspective on the audio signal, capturing essential characteristics that reflect emotional states. By combining these features into a comprehensive representation of speech, emotion recognition models can achieve higher accuracy, paving the way for effective real-time human-computer interaction systems.

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