Experiments on Emotional Speaker Recognition

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Outline

- 1. Introduction
- 2. Speaker Database Design
- 3. E-Norm Algorithm
- 4. Pitch Based Clustering Algorithm

Introduction

 When the emotion states mismatch between the training and testing speech, the capability of speaker recognition(SR) will be significantly decreased

 The emotional speaker recognition is the task to improve the robustness of SR on the emotions

Influence Factors

Due to the speaker affected by the content of the sentence

• Due to the content of the sentence affected by the emotion of the speaker

Database Design

• Emotion Type

-Neutral, Happiness, Sadness, Anxiety, Anger

• Syllables Coverage

- -21 initials and 38 finals
- —About 500 kinds of syllables

Content Scripts

- —Emotional scripts
- -Neutral scripts

E-Norm

 Norm algorithms are to decrease the mismatches between the models and the testing features

Assumption: The scores from one speaker follow a Gaussian distribution

E-Norm

- Training Data Set
 - Train the parameters for the normalization
- Testing Data Set
 - Neutral: Including some utterances used in training data set
 - Other emotions: different from the training data set

E-Norm Result

| E-Norm | Whole | | Male | | Female | |
|--------|--------|-----------|---------|-----------|---------|-----------|
| | EER | Threshold | EER | Threshold | EER | Threshold |
| Whole | 19.98% | -0. 8682 | 27.96% | -0. 5685 | 27.25% | -0. 6544 |
| NL | 5.04% | -1. 5824 | 8. 21% | -1.3874 | 7. 23% | -1. 3966 |
| НР | 21.63% | -0. 7279 | 29.72% | -0. 3886 | 30. 21% | -0. 3995 |
| SD | 21.89% | -0. 8557 | 31.81% | -0. 4137 | 28. 22% | -0. 7672 |
| AX | 22.01% | -0.7456 | 31.90% | -0. 4548 | 28. 71% | -0. 4682 |
| AG | 26.09% | -0. 7432 | 34. 49% | -0. 4659 | 35.77% | -0. 4954 |

E-Norm Results

| | Whole | Male | Female | |
|-------|---------|---------|---------|--|
| Whole | 20. 56% | 15. 99% | 17.60% | |
| NL | 51.86% | 49.54% | 36. 91% | |
| HP | 10.29% | 5. 29% | 7.84% | |
| SD | 10.32% | 2.96% | 4. 31% | |
| AX | 6. 10% | 4. 49% | 1.91% | |
| AG | 4. 78% | -1. 98% | 0.94% | |

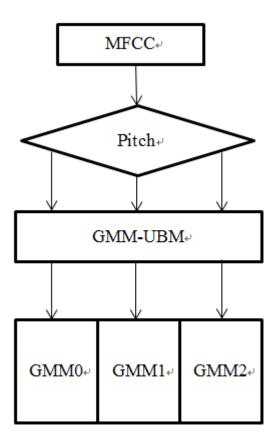
Relative improvements

Pitch-Based Clustering

 Clustering on frames of features

• Each group training into a GMM

• 3 GMMs



Pitch Clustering

| | Male(Hz) | Female(Hz) |
|--------|----------|------------|
| Group1 | 0–120 | 0–120 |
| Group2 | 120–196 | 120-290 |
| Group3 | >196 | >290 |

Score Fusion

- Average(Score1 + Score2 + Score3)
- Max(Score1, Score2, Score3)

Results

| | Whole | | Male | | Female | |
|-------|---------|-----------|---------|-----------|---------|---------|
| Best | EER | TH | EER | TH | EER | TH |
| Whole | 18.40% | 0. 3333 | 19. 76% | 0. 311367 | 28.13% | 0. 4977 |
| NL | 14. 18% | 0. 386433 | 18.81% | 0.362033 | 21.11% | 0. 5098 |
| HP | 19.97% | 0. 3777 | 18.66% | 0. 3211 | 25.63% | 0. 6117 |
| SD | 16. 56% | 0. 273267 | 19.85% | 0. 293967 | 23. 56% | 0. 36 |
| AX | 16. 37% | 0. 310367 | 16. 22% | 0. 286033 | 25.93% | 0. 4847 |
| AG | 21.41% | 0. 341533 | 20.88% | 0. 299767 | 32. 52% | 0. 5018 |

- For male, Group1 gives the best EER
- For female, Group2 gives the best EER
- The erformance of male is better than female

Thanks!